

**Better performance of mutual funds with lower R^2 's
does not suggest that active management pays**

Juan Carlos Matallín-Sáez*

December 8, 2020

Abstract

We found a negative relation between mutual funds' past R^2 and their abnormal performance, as did Amihud and Goyenko (2013), who proposed measuring active management of mutual funds by $1-R^2$. The interpretation of this relationship would be that active management pays. However the same evidence is uncovered for artificial investments, due only to the behavior of the types of stocks they are holding. Therefore, we introduce a new factor, *ImS* (idiosyncratic minus systematic), defined as the difference between the stocks' returns with lower and higher past R^2 which captures this behavior. After adjusting for this factor, the initial evidence vanishes and abnormal performance associated with past R^2 diminishes, even taking negative values for mutual funds.

Key words

Performance, idiosyncratic risk, R squared, mutual fund, active management

JEL Code: G23, G11

* This study is part of the research projects ECO2017-85746-P supported by the Spanish Ministerio de Economía y Competitividad and UJI-B2017-14 supported by Universitat Jaume I. Address for correspondence: Juan C. Matallín-Sáez, Department of Finance and Accounting, Universitat Jaume I, E-12080 Castellón, Spain. Tel: +34 964 387 147, Fax: +34 964 728 565. E-mail: matallin@uji.es. I thank Laura Andreu, J. David Moreno, J. Luis Sarto and Amparo Soler for their helpful knowledge on financial databases. The usual disclaimer applies.

1. Introduction

The growth of the mutual fund industry has spawned a field of study on asset pricing and portfolio management. One of the most debated issues is mutual fund performance, that is, whether active management is able to add value for investors. Ferson (2010) and Elton and Gruber (2013) provide reviews of this literature. In this context, an interesting approach is to analyze the level of active management of the funds and its effect on performance. Amihud and Goyenko (2013) measure active management of mutual funds by $1-R^2$, i.e. the proportion of the fund's variance that is due to idiosyncratic risk or multifactor tracking error variance. They form portfolios that invest in mutual funds according to their past R^2 and, in general, find a negative relationship between past R^2 and performance. They therefore argue that investing in funds with higher past active management predicts better performance.

First, for a sample of 17,775 US equity multi-share mutual funds and for a period of over 25 years—January 1990 to June 2015—we apply an algorithm forming quintile portfolios that invest in mutual funds according to their past R^2 . We find a negative relationship between past R^2 and abnormal performance that confirms Amihud and Goyenko's (2013) results in a larger and more recent sample. Second, we apply the same procedure to stocks instead of mutual funds, finding exactly the same abnormal rate of return patterns. However, stocks are not portfolios managed as mutual funds, so in this case the negative relationship between past R^2 and abnormal performance is not due to active management by mutual funds. Therefore, the mutual fund evidence could be an implicit effect of the assets in which the funds invest.

When different subperiods are analyzed, the sign of the relationship between past idiosyncratic risk and performance for mutual funds holds positive for 1990-2007 but negative for the latter part of the sample period, 2008-2015. We find the same time pattern for the R^2 of mutual funds and artificial investments. So, both the R^2 of the mutual funds and their performance obtained from strategies based on past R^2 can be significantly explained by the sets of artificial portfolios. Moreover, we found that investment strategies based on past R^2 of artificial portfolios provide a superior performance to that achieved by the same strategies for the case of mutual funds.

However, on this comparison, it is important to point out that, unlike mutual funds, the artificial portfolios are not bearing trading costs.

Inspired by the approach of previous studies, such as Carhart (1997) and Jordan and Riley (2015), we propose a factor named *ImS* (idiosyncratic minus systematic), and defined as the difference between the stocks' returns with lower and higher past R^2 . This factor captures the returns of investment strategies based on past R^2 and, moreover, the previous evidence disappears; i.e. when the *ImS* factor is included, abnormal performance diminishes, so the alphas for quintile portfolios from mutual funds become negative. The effect of including this new factor is similar to that in Carhart's study when the *WmL* (winners minus losers) factor was introduced. Carhart shows how the previous evidence in persistence found by Hendricks et al. (1993) is mostly driven by the one-year momentum effect of Jegadeesh and Titman (1993). Also in this line, Jordan and Riley (2015) introduce the *LVH* factor, defined as the difference in the return between stocks with low and high volatility. When this factor is considered, the previous evidence that low volatility funds perform better disappears.

These results tell us that it is mistaken to argue that the documented abnormal rate of return and R^2 relationship among mutual funds is necessarily related to activeness vs. passiveness. Indeed, it could just be due to the types of stocks that different mutual funds are holding. The financial literature analyzing mutual funds has shown how empirical evidence initially attributable to active management is actually a passive effect due to the behavior of underlying assets not captured by the proposed model¹: (a) regarding mutual fund abnormal performance (Elton et al. 1993, Pástor and Stambaugh 2002, Phalippou 2014 and Jordan and Riley 2015); (b) regarding the evidence of mutual fund persistence (Carhart 1997, Gottesman and Morey 2007 and Fama and French 2010); (c) relating to market timing, i.e. the ability to anticipate stock market behavior (Jagannathan and Korajczyk 1986, Bollen and Busse 2001 and Matallín-Sáez et al. 2015); (d) Sapp and Tiwari (2004) show that the “smart money” effect (mutual fund

¹ The meaning of active or passive management is related to the use of these terms in the context of performance models. Factors *SmB*, *HmL* in Fama and French (1993), *WmL* in Carhart (1997), *LVH* in Jordan and Riley (2015), or *ImS* in this paper imply active management because they are constructed by buying and selling certain stocks with regular rebalancing. However, in the performance model these factors represent the passive management (analogous to a benchmark in Jensen 1968) with which to compare and adjust the returns of the fund. Therefore, fund managers who seek to replicate a factor would carry out active management, but for the purposes of the performance model it would be considered passive since it does not differ from the factor.

selection ability of investors) documented by Gruber (1996) and Zheng (1999) is explained by the stock return momentum effect documented by Jegadeesh and Titman (1993), and (e) regarding the inverse relation between fees and performance (Sheng et al. 2019 considering the Fama and French 2015 five-factor model). All these papers found new and different evidence to that of the previous literature. Our results therefore suggest that the present study could fall within this stream of literature. Appendix 1 (in web annex) demonstrates how an omitted factor works, and its effect on performance and idiosyncratic risk

The remainder of the paper is organized as follows. Section 2 describes the methodology used to measure performance, the algorithm to form and evaluate investment strategies based on past R^2 , and the procedure to estimate synthetic funds. Section 3 describes the data sets used: mutual funds and artificial investments. Section 4 contains the empirical results: first the main results and second, the robustness and additional analyses. Section 5 discusses the main conclusions of the study.

2. Methodology

2.1 Performance measurement

The main purpose of this study is to analyze the performance of investment strategies based on past R^2 . To do this, first a model must be applied to adjust portfolio returns and compute R^2 . Following standard procedures from a large body of literature on portfolio performance assessment, we regress portfolio returns and measure abnormal performance applying different linear models by means of Equation (1), where $r_{p,t}$ is the excess return over the risk free asset of the portfolio p , the term α_p measures the abnormal performance once the portfolio return has been adjusted to the return $r_{j,t}$ of J risk factors, and $\varepsilon_{p,t}$ is the error term of the model.

$$r_{p,t} = \alpha_p + \sum_{j=1}^J b_j r_{j,t} + \varepsilon_{p,t} \quad (1)$$

Specifically, we consider three different models for robustness. The first, the *4F model*, includes the Fama and French (1993) three factor model: the excess market return $r_{m,t}$; the return of small stocks minus the return of big stocks $r_{smb,t}$ and the difference of the return between higher and lower book-to-market ratio stocks $r_{hml,t}$; a momentum factor is

also included, namely, the return of past winners minus past losers $r_{wml,t}$ proposed by Carhart (1997). This model has been widely applied in the recent mutual fund literature by Fama and French (2010), Busse et al. (2010), Ferreira et al. (2012) and Phillips et al. (2016) among others. The *5F model* is by Fama and French (2015) and incorporates two additional factors into the three factor model: $r_{rmw,t}$ the difference between the returns on diversified portfolios of stocks with robust and weak profitability, and $r_{cma,t}$ the difference between the returns on diversified portfolios of the stocks of low and high investment firms, which we call conservative and aggressive. Finally, Cremers et al.'s (2013) *7F model* is considered, which compared with the *4F model*, replaces HML and SMB factors with five factors named mid minus big, $r_{mmb,t}$ small minus mid $r_{smm,t}$, big high book-to-market ratio minus big low book-to-market ratio, $r_{bhml,t}$, and similarly, small high minus small low, $r_{shml,t}$, and mid high minus mid low, $r_{mhml,t}$.

2.2 Investment strategies based on past R^2

To compute past R^2 and estimate performance we apply a recursive portfolio approach similar to Carhart (1997). This methodology is very common in finance and consists of forming portfolios based on some past attribute of the mutual funds. Specifically, we assess the performance of portfolios that invest following strategies based on the level of the past R^2 . Therefore, we propose applying a recursive portfolio approach by means of the following algorithm (Algorithm I):

1. For the previous two years' data we apply Equation (1) for the assessed portfolios.
2. We rank portfolios in increasing order according to the R^2 they achieved in the period to form quintiles. In some cases the ordering is performed on the whole portfolio set in the sample, and in other cases it is performed within a subset of portfolios grouped according to style.
3. At the beginning of the next month we form five equally-weighted portfolios according to the above quintiles. Hence, the first quintile portfolio, *Low*, invests in the mutual funds with the lowest past R^2 and, conversely, the last quintile portfolio, *High*, invests in the previous mutual funds with the highest R^2 . The same pattern is followed for the other quintiles.
4. This procedure is repeated at the beginning of each month (i.e., restarting at step

1), so that each quintile portfolio represents an investment strategy that *rebalances* selected portfolios according to their previous R^2 .

5. We therefore compute the returns of each quintile portfolio and then estimate its abnormal performance, also using model (1).

First, we applied Algorithm I to mutual funds. Amihud and Goyenko (2013) use the percentage of idiosyncratic risk ($1-R^2$) as a measure of the active management of mutual funds and hypothesizes that if active management enhances mutual fund performance, it should be negatively related to R^2 and then a quintile portfolio which invests based on a low (high) past R^2 will show a positive (negative) abnormal performance. However, we refine this proposal since artificial investments can also have idiosyncratic risk simply because they are not an exact combination made up of the risk factors in the model (1). Therefore, $1-R^2$ would not be synonymous with active management.

Secondly, we also apply Algorithm I to various sets of not professionally managed investments and analyze the results comparing them with those achieved by the mutual funds. As stated in Appendix 1 (in web annex), we hypothesize that if artificial portfolios' performance is also negatively related to their past R^2 , part of the evidence found in the mutual funds could not be driven by active management but by a passive effect between the idiosyncratic risk of the stocks in the portfolio and their subsequent performance. With this aim, we consider several sets of investments that are not professionally managed: a sample of stocks and portfolios formed from these stocks, different portfolios from French's data library and a set of synthetic portfolios where, following Sharpe (1992), each mimics the style of its mutual fund counterpart. To save space, the estimation procedure of this last set of artificial portfolios is shown in the web annex.

3. Data

3.1 Mutual fund and factor data

Daily return data, available from 1990, of US domestic equity mutual funds are taken from the Morningstar database. The study sample period covers more than 25 years, from January 1990 to June 2015. There is no survivorship bias because the sample

includes both new and non-survivor funds². We initially considered 17,775 multi-share mutual funds. To provide robustness to the estimation of model (1) and the problem defined by equations (2)-(5) in the web annex and considering the recursive nature of Algorithm I, the final sample contains only funds with data for at least eighteen months during the sample period. The final sample contained 15,059 multi-share funds. Following standard procedure, multiple share classes were aggregated as one single unit, or mutual fund, giving a final sample consisting of 4,467 mutual funds. To explore robustness over time and in different stock market states, we split the period sample into three subperiods, coinciding with moments of pre- and post-financial crisis. The first subperiod runs from 1990 to 1997, the second from 1998 to 2007 and the third from 2008 to 2015.

To add further robustness to our analysis, in addition to applying Algorithm I for all funds in the sample, we also apply it separately to each mutual fund type. The mutual funds are grouped according to their style as defined by the Morningstar Style Box. As Teo and Woo (2004) show, Style Box is a useful tool to analyze mutual fund management due to different characteristics of the underlying stocks. Hence, we are interested in checking whether the results for the relationship between past R^2 and performance hold in all mutual funds styles, or whether the evidence depends to some degree on the style and not only on managers' ability.³

To apply expression (1), the one-month Treasury bill rate as the risk free asset, the returns of the three and five Fama and French factors and the other factors from Cremers et al. (2013) were taken from French's library.⁴

3.2 Artificial investments data

As noted above, because passive portfolios can also have idiosyncratic risk it is interesting to also apply Algorithm I to various sets of artificial investments and analyze

² As Elton et al. (2001) pointed out, the most widely used mutual fund databases in recent studies are those provided by the Center for Research in Security Prices (CRSP) and Morningstar. They conclude that tests of various mutual fund issues might be conditional on the data that researchers use. In this sense Amihud and Goyenko (2013) used the CRSP database and in this paper we have used the Morningstar database. However, despite these differences, our results for mutual funds are similar to those achieved by Amihud and Goyenko (2013). Hence, rather than contradicting their paper, our contribution in fact complements it. Although Elton et al. (2001) pointed out that the Morningstar database has survivorship bias, this is no longer the case for recent versions of this database (Morningstar Direct).

³ To save space, descriptive statistics of the data reported in this section are shown in the web annex.

⁴ http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

the results. We considered several sets of investments that are not professionally managed. The first set of artificial investments, *Stocks*, is formed for a sample of equities traded on the NYSE, AMEX and NASDAQ stock markets, also from January 1990 to June 2015. Daily return is computed from the *daily market index return* taken from the Morningstar database. There is no survivorship bias because the sample includes both currently listed and non-listed equities. As in the case of mutual funds, to provide robustness the final sample contains only stocks with data for at least eighteen months during the sample period. The final sample is composed of 10,973 stocks.

The second and third set of artificial investments is made up of portfolios formed randomly from this stock sample. To compare these artificial investments with mutual funds, we create the same number of portfolios as our sample of funds. Specifically, we created 4,467 equally weighted portfolios (*EW stock portfolios*) and another 4,467 value weighted portfolios (*VW stock portfolios*). These portfolios select stocks randomly and follow a passive buy-and-hold strategy, but they do not always invest in the same number of stocks because the number of listed stocks in the market changes frequently. Also for comparative purposes these portfolios are formed with characteristics that are very similar to mutual funds⁵.

The next two sets are made up of 300 portfolios from French's data library. Specifically, they are 100 portfolios combining 10x10 deciles based on *size* and *book-to-market* values, 100 formed on *size* and *operating profitability* and 100 formed on *size* and *investment*. Since the portfolios are periodically rebalanced based on time variations in the sorting characteristics, it could be argued that these portfolios involve some sort of active management. However, in reality they simply group stocks by different characteristics, in the same way that might be done for instance, in analyses with an industry and geographical focus, and in these cases no active management is considered.

⁵ In this line, Shawky and Smith (2005) find that for the period 1990-2000, on average, mutual funds hold 91 stocks, weighting 33.52% the 10 top holdings. For the period 1990-2009, Gallagher et al. (2014) find that mutual funds hold an average of 110 stocks in their portfolios. Therefore, although the funds have a large number of stocks to invest in, they prefer to select a sufficiently large number to allow the benefits of diversification but at the same time low enough to not raise the costs of monitoring these stocks (Shawky and Smith 2005). First, in the case of *EW stock portfolios*, the number of stocks that they hold is determined randomly. Panel A shows that on average these portfolios invested in 148.79 stocks during the period 1990-2015. The average of the minimum (maximum) number of stocks in which they invested was 85.87 (179.70). In the case of the *VW stock portfolios*, the stock weighting is a function of their market capitalization, but ensuring the diversification of the portfolio, therefore truncating the higher weights and properly rescaling. For these portfolios the average number of stocks held was 139.70 and the average of the minimum (maximum) number of stocks was 64.58 (177.91). Accordingly the portfolios are diversified, the maximum weighting being 3.70%, and the average of the lowest (highest) maximum weight 2.92% (5.97%).

Moreover, the artificial nature of our portfolios is defined by the absence of active management, i.e. these portfolios are not handled by managers with investment abilities such as, among others, stock picking (buying undervalued and selling overvalued stocks) and market timing (anticipating stock market movements). The sixth set of artificial investments, *French Industries portfolios*, is formed by sorting stocks according to their industrial sector. It is made up of 98 value and equally weighted portfolios and also comes from French's data library. The seventh is a set of *synthetic funds* that, following the methodology proposed by Sharpe (1992), replicate the style of the mutual funds in the sample. To save space, the results of estimating synthetic funds are presented in the web annex.

4. Results

4.1 Measuring predictability of R^2 in mutual funds, stocks and the *ImS* factor

Using first the 4F model we follow Algorithm I to form quintile portfolios according to past R^2 and estimate their abnormal performance. The first (last) quintile portfolio, *Low (High)*, invests in the mutual funds with lowest (highest) past R^2 . Table 1 presents the results for the whole sample period, from 1990 to 2015. The last column shows the estimation for the *Low* minus *High* portfolio. The performance decreases monotonically across quintile portfolios as past R^2 increases. In fact, the difference between the performance of the *Low* and *High* quintile is 1.4% and significant. However, it must be noted that even though the *Low-High* quintile is useful to show differences, it does not represent a feasible investment strategy since it is very hard to short sell mutual funds. Thus, it is interesting to note that the performance of the feasible strategy using funds with *Low* R^2 does not add value for investors since that abnormal performance in Table 1 is -0.37%.

The results point to an inverse relation between past mutual funds' R^2 and future performance. This confirms Amihud and Goyenko's (2013) findings, despite differences in mutual fund databases. If we assume the hypothesis that the percentage of idiosyncratic risk is due to a mutual fund's active management (Amihud and Goyenko, 2013) a positive relationship could be inferred between the level of active management and performance.

However, if idiosyncratic risk is caused in a passive manner, i.e. from the aggregated idiosyncratic risk of the underlying assets, the relationship between past R^2 and performance would not be attributable to managers' ability, but to the behavior of those assets. In order to address this issue we also apply Algorithm I to the *Stocks* investment set in the sample. In this case, there is no difference in how active or passive the five portfolios are; they just contain different types of stocks and are not professionally managed. The results, shown in Table 2, point to a negative relationship between past R^2 and performance similar to that found in Table 1 for mutual funds.

As a possible additional factor in the performance model, we then consider a mimicking portfolio for the relationship between past R^2 and performance. This factor is in line with Carhart (1997) and Jordan and Riley (2015), who propose additional factors to capture the behavior of mutual funds due to stocks' behavior. To do so they applied a methodology very similar to our Algorithm I. Thus, in steps 1 and 5 of the algorithm, model 4F is applied adding *ImS* as an additional factor⁶. The results for the whole sample period are shown in Table 3, then after incorporating the *ImS* factor, the inverse relationship between past R^2 and abnormal performance found in Table 1 for mutual funds disappears.

As in the Carhart, and Jordan and Riley studies, the inclusion of an additional factor closely related to the issue analyzed modifies the initial results. Carhart explores whether mutual funds' past performance conditions future performance and includes the *momentum* factor in which the past return of stocks conditions future return. Jordan and Riley analyze how past mutual fund volatility conditions future performance, and include the low minus high volatility factor in which the past volatility of the stocks conditions future return. In our paper, we analyze whether mutual funds' past R^2 conditions future performance and include the *ImS* factor in which the past R^2 of stocks conditions future performance. We consider noteworthy the parallel between our results

⁶ Our additional factor will be the difference between the stocks' returns with lower and higher R^2 in the past. This factor coincides with the return of the *Low-High* quintile portfolio for the case of the *Stocks* investment set. To avoid confusion with other factors, we named this factor *ImS*, idiosyncratic minus systematic, since it is the difference in return of stocks that in the past had a higher percentage of idiosyncratic risk, that is, lower R^2 or a lower percentage of systematic risk, with respect to those with higher R^2 . Since the introduction of the CAPM, the asset pricing literature has developed by incorporating new factors linked to a single characteristic or variable with explanatory power, such as size (*SmB*) and book-to-market ratio (*HmL*) in Fama and French (1993), and momentum (*WmL*) in Carhart (1997). In contrast, the *ImS* factor captures the effect of a greater number of characteristics or variables that are omitted and that are implicitly captured by the idiosyncratic risk.

and those of Carhart, and Jordan and Riley, both in the methodology applied and in the implications derived from the results.

4.2 Robustness and additional analyses

4.2.1 Considering subsamples, other performance models and artificial investments

In the previous section we showed that there is a negative relation between past R^2 and abnormal performance for mutual funds; however, this same relation is found for an artificial investment, such as stocks. Thus, considering a factor that captures the relation between past R^2 and performance, the previous evidence for mutual funds vanishes. For robustness purposes, in this section we now re-analyze these issues considering other performance models and subsamples. We also test the relationship between past R^2 and abnormal performance for different sets of artificial investments. To save space, rather than showing the results for all quintile portfolios, only the difference in the performance between the *Low* and *High* quintile portfolios is provided.

Column (1) of Table 4 presents the results for mutual funds. As Table 1 showed for the 4F model, the difference between the annualized abnormal performance of the *Low* and *High* quintile is 1.4% and significant in Panel A of Table 4. The evidence is similar when 5F and 7F models are applied. Panels B, C and D of Table 4 allow us to analyze performance in different subperiods. For the two earlier subperiods, 1990-1997 and 1998-2007, the differences between *Low* and *High* quintile portfolios are positive and significant. However, in Panel D the evidence is different for the most recent sample subperiod, January 2008 to June 2015, taking negative values and, depending on the model considered, lacking significance. Our results are consistent with Amihud and Goyenko (2013), despite differences in mutual fund databases or period samples.⁷

The next columns of Table 4 show the results of applying Algorithm I for different sets of artificial investments, i.e. without professional active management. The results show,

⁷ Also using daily data, Amihud and Goyenko (2013), indicate that the different results in the last part of the sample might be influenced by the 2008 financial crisis. They remove these data from the sample in such a way that the results are more similar to those obtained in the first part of the sample, so that fund's R^2 is a significant predictor of its subsequent performance.

in general, an inverse relation between past R^2 and future performance,⁸ supporting the results shown in Table 2. When stocks are held by portfolios, idiosyncratic risk is weighted and reduced by diversification; consequently this relationship is evidenced with less intensity at the portfolio level, although it maintains its sign and significance in most cases. Depending on how the stocks in the portfolio are selected, this relationship will manifest itself differently. Specifically, the effect of higher past percentage of idiosyncratic risk and superior performance is stronger for: (a) equally weighted portfolios because this effect is more intense for small stocks; (b) portfolios that group stocks according to common characteristics (size, book-to-market, operating profitability and investment) rather than randomly or by industrial sector.

4.2.2 The time pattern of R^2 and performance for active and artificial investments

From the previous section it can be deduced that both actively managed portfolios, such as mutual funds, and artificial investments show, in general, an inverse relationship between past R^2 and performance, i.e. a positive relationship between the past percentage of idiosyncratic risk and performance. Following on from this, it is interesting to analyze the time pattern of R^2 . If the evolution over time of the mutual funds' R^2 is similar to that experienced by the artificial investments, it will indicate that part of the percentage of idiosyncratic risk in mutual funds is due not to managers' activity, but to the behavior of the level of idiosyncratic risk of the stocks in the funds' portfolios.

With this aim, when Algorithm I was applied, we saved the R^2 values obtained for each individual investment within each of the sets analyzed: *Mutual funds*, *Stocks*, *VW* and *EW stock portfolios*, *French VW* and *EW portfolios*, *French Industries portfolios* and *Synthetic funds*. Each line in Figure 1 displays the average values of the R^2 for each set of investments through the application of the 4F model in Algorithm I. As expected, the

⁸ In relation to this issue, it should be noted that our results are different to the evidence from Amihud and Goyenko's (2013) analysis of passive portfolios. In section 7 of their study (pages 684-685) these authors use a set of 100 passive portfolios and another set of 48 industry portfolios. But what is relevant is that they do not use the methodology applied to mutual funds in Table 2 (in page 673) to these sets of passive portfolios, but instead they apply the methodology used in Table 4 in another additional robustness analysis. We consider that the relevant contribution of Amihud and Goyenko's work emerges from the results of Table 2, i.e., when they assess the performance of the investment strategies based on past R^2 . We think that the logical framework for robustness analysis would have been to apply exactly the same methodology with both the active mutual funds and the passive portfolios data. For instance, to cite a work from the mutual fund literature, Bollen and Busse (2001) on page 1089, Table III, use exactly the same methodology for both data: Panel A shows results for the mutual fund sample and Panel B, for the synthetic funds. In this line, in our paper, we apply exactly the same methodology to mutual funds as the artificial portfolios.

lowest values of R^2 are obtained for the set of *Stocks*, that is, for the individual stocks. In no case does the average value of R^2 exceed 30%; it increases over time, especially in the last third of the sample period. The behavior of the R^2 of the stocks is reflected in the rest of the investments. Due to the effect of diversification, the R^2 for portfolios is higher than for stocks. The portfolios with the lowest R^2 values are the set of *French Industries* and, from bottom to top in the chart, the *French VW* and *EW portfolios*. As seen in the figure, the portfolios with the most similar R^2 to the set of *mutual funds* are the *VW* and *EW stock portfolios*. Especially for the set of the *VW stock portfolios*, both the level of R^2 and its behavior over time is very similar to that shown by mutual funds. Recall that except for the case of mutual funds, the other investments displayed in Figure 1 are not professionally managed. Therefore, it can be deduced that, in aggregate, the behavior of the R^2 of mutual funds is similar to that shown by stocks and artificial portfolios.⁹

We proceeded to analyze the behavior of the R^2 shown in Figure 1 in a more quantitative way. First, to avoid the overlapping of the windows characteristic of Algorithm I, we again applied models 4F, 5F and 7F but using a non-overlapping 2-month rolling window. This estimate was also made individually for every mutual fund and artificial investment. From this data, we compute the linear correlation between the average of R^2 of the regressions for mutual funds and those corresponding to each set of artificial investments, their significance and their value squared. To save space, the results are incorporated in the web annex. For instance, the correlation between the mutual funds' R^2 and the *French VW portfolios* is 0.966. From this it follows that 93.3% of the variation of the percentage of idiosyncratic risk of the mutual funds would be explained by the changes in the percentage of idiosyncratic risk of the artificial portfolio. It is noteworthy that for all models these values are high. In general the explanatory power of artificial investments on mutual fund R^2 is high.

We also explore the time pattern of the performance linked to past R^2 of mutual funds and artificial portfolios. To save space results are reported in the web annex. The

⁹ The evidence shown in Figure 1 is in line with Figure 1 in Jordan and Riley's (2015) study, which displays the value of one dollar invested in mutual funds sorted on past return volatility. In this figure, the decile portfolios from low to high past volatility also show a common pattern time. This behavior suggests that rather than management activity, there is an artificial effect of the mutual fund stocks, which simply contribute less or more volatility to the fund. In fact, Jordan and Riley (2015) would later show how the relationship between past volatility and performance is not due to fund manager skill.

evidence elicits two comments: first, that the performance achieved by mutual funds according to their past R^2 is related to that obtained by an artificial investment, that is, by the underlying assets; and second, that in light of the negative intercept in regressions, it is worse, from the investor's perspective, than that achieved only by artificial investments (a result that is in line with those shown in Table 4). However, it is appropriate to clarify that no trading costs for artificial investments or sales charges and load fees for mutual funds have been considered.

4.2.3 Style effects in active and artificial investments

To save space, the results of this section are incorporated in the web annex; only the main conclusions are commented on below. Firstly we analyze whether the evidence found in column (1) of Table 4 on the predictive capability of the past R^2 holds across mutual fund styles. Results reveal that the evidence found in Table 4 for the whole mutual funds sample does not hold for all styles of funds but only for certain cases. In general, for the whole of the sample period only small value, mid-cap blend and large growth styles show positive and significant performance in investment strategies based on past R^2 .

Secondly we analyze the size effect on the results for *French VW* and *EW* artificial portfolios by grouping them in deciles according to the size of their stocks; this analysis shows that the negative relationship between R^2 and future performance is only found when small and small-medium styles are considered, and in general only for the two first subperiods. We found that all quintile portfolios within the low size decile achieve a remarkable positive performance. As these portfolios are formed by the smallest stocks, this result could be explained by the performance of microcap¹⁰ stocks which gain weight in the case of equal weighting. Thirdly, mutual funds and synthetic funds grouped by style are compared. For practically all styles the performance achieved for the *Low-High* quintile portfolios based on past R^2 of mutual funds is lower than that based on past R^2 of synthetic funds.

¹⁰ We are grateful to Professor Kenneth R. French for this valuable suggestion about how returns in small equally-weighted portfolios are being driven by microcaps. The usual disclaimer applies.

4.2.4 Volatility, idiosyncratic volatility and R^2

We analyze the relations between the percentage of idiosyncratic volatility, $1-R^2$, volatility and idiosyncratic volatility in the context of our results and the previous literature. Below we show the most relevant results. An expanded version of this section can be found in the web annex.

For mutual funds, the correlation between $1-R^2$ and volatility is low (0.18). This means that investment strategies based on selecting mutual funds according to the level of $1-R^2$ (Amihud and Goyenko 2013 and this study) can provide different results with respect to those based on the level of volatility (Jordan and Riley 2015). On the other hand, the correlation between $1-R^2$ and idiosyncratic volatility is higher (0.60), which implies that investment strategies based on these variables could provide similar results. For mutual funds, Amihud and Goyenko (2013) and our study find a positive relationship between past $1-R^2$ and performance. We also find the same positive relationship for several sets of artificial portfolios from French's data library, a set of synthetic portfolios, and a sample of stocks. However this evidence seems to be at odds with Ang et al. (2006), who find a negative relation between past idiosyncratic volatility and performance for stocks.

We consider some issues that may be relevant to account for the different results for the relationship between these variables for stocks. Firstly, although $1-R^2$ and idiosyncratic volatility are related, their correlation for the stocks sample is low (0.32), which could allow different results for investment strategies based on them. Secondly, previous literature (Bali and Cakici 2008, Huang et al. 2010, Han and Lesmond 2011, Malagón et al. 2013 and Schneider et al. 2020) has pointed out that the negative relation found by Ang et al. (2006) depends on liquidity, skewness, small stocks, idiosyncratic volatility estimation, data frequency, the value-weighted scheme forming portfolios, and the sample period, among other issues. Thirdly, we compare the stocks database used in this research (Morningstar Direct) with that used by the previously cited asset pricing studies (CRSP). We found relevant differences in the stocks covered by the databases, which could explain the different results for the relation between past idiosyncratic volatility and performance for stocks.

4.2.5 Other additional analysis

The web annex includes several additional analyses not previously mentioned. (a) When in Algorithm I we consider a two-month instead of a two-year rolling window, results are similar. (b) As we show in Appendix 1 of the web annex, the idiosyncratic risk can capture the effect of factors omitted in the performance model and with explanatory power on the returns of the underlying assets in a portfolio. Aside from the *ImS* factor, we also consider the inclusion of the aggregate volatility and previous results are not modified. (c) We explore the role of fund costs using gross returns in Algorithm 1. The inverse relationship between past R^2 and abnormal performance holds. The correlation between the average expense ratio and the mutual funds' R^2 for the entire sample period is -0.24. Therefore, the abnormal performance of *Low-High* past R^2 quintile portfolio is higher with gross returns (1.85%) than for the case of net returns in Table 1 (1.40%). Also Algorithm 1 is applied using gross returns and model 4F with the *ImS* additional factor and the same evidence is found as when net returns are used: the inverse relationship between past R^2 and abnormal performance vanishes. In sum, the previous evidence using net returns holds and is not driven by expenses. (d) A comparison of the performance linked to past R^2 of mutual funds and artificial portfolios reveals that the abnormal performance for mutual funds (from the perspective of the funds' investors but without considering sales charges and load fees) was not different from, or was even worse than, that obtained by the same investment strategies in artificial portfolios (without considering transaction costs). (e) We also carried out the main analysis of this study, but grouping portfolios by two dimensions: past R^2 and past loading of the *ImS* factor. As expected, portfolios with a higher (lower) percentage of idiosyncratic risk exhibit higher (lower) loading on the *ImS* factor. As was the case in Table 3, where the *ImS* factor is included, strategies based on past R^2 do not generally provide a positive abnormal performance.

5. Conclusions

This study belongs to a part of the mutual fund performance literature that analyzes how some of the evidence previously attributed to mutual fund active management can be explained by the behavior of the assets in which the fund invests (Jagannathan and Korajczyk 1986, Carhart 1997, Pástor and Stambaugh 2002, Phalippou 2014, Matallín-Sáez et al. 2015 and Jordan and Riley 2015, among others).

In particular, we examine the relation between a fund's factor model regression R^2 and its performance. For a sample of US domestic equity mutual funds, the study covers more than 25 years, from January 1990 to June 2015. In line with Amihud and Goyenko (2013) the results show a negative relationship between past R^2 and abnormal performance. As Amihud and Goyenko (2013) proposed measuring active management of mutual funds by $1-R^2$, i.e. the level of idiosyncratic risk, they then argue that active mutual fund managers have higher average rates of abnormal return than passive managers. However, if idiosyncratic risk is caused in a passive manner, i.e. from the aggregated idiosyncratic risk of the underlying assets, the relationship between the percentage of idiosyncratic risk and performance would not be attributable to managers' ability, but to the behavior of those assets. In order to address this issue we also analyze this relation for a sample of stocks, finding a stronger relationship between R^2 and performance.

Then, as a possible additional factor in the performance model, we consider a mimicking portfolio for this relationship. In this factor, named *ImS* (idiosyncratic minus systematic), the past percentage of idiosyncratic risk of stocks conditions future performance. Our results reveal that when the *ImS* factor is introduced, the initial evidence of a negative relationship between past R^2 and performance for mutual funds vanishes.

For robustness purposes, this study also analyzes this relationship for different sets of artificial portfolios. In this case, we also found, in general, a negative relationship between past R^2 and abnormal performance. It is clear that this evidence cannot be due to professional active management. Moreover, when we compared mutual funds with artificial portfolios, we found that the behavior of the R^2 and performance of the mutual funds is significantly explained by the artificial investments. We found that the artificial portfolios' performance is more strongly related to R^2 . They also perform better than mutual funds.

5. References

- Amihud, Y. and Goyenko, R. (2013), Mutual fund's R^2 as predictor of performance, *Review of Financial Studies* 26(3), 667–694.
- Bali, T.G. and Cakici, N. (2008), Idiosyncratic volatility and the cross section of expected returns, *Journal of Financial and Quantitative Analysis* 43(1), 29–58.

- Bollen, N. P. B. and Busse, J. A. (2001), On the timing ability of mutual fund managers, *Journal of Finance* 56(3), 1075–1094.
- Busse, J. A., Goyal, A. and Wahal, S. (2010), Performance and persistence in institutional investment management, *Journal of Finance* 65(2), 765–790.
- Carhart, M. M. (1997), On persistence in mutual fund performance, *Journal of Finance* 52(1), 57–82.
- Cremers, M., Petajisto, A. and Zitzewitz, E. (2013), Should benchmark indices have alpha? Revisiting performance evaluation. *Critical Finance Review* 2(1), 1–48.
- Elton, E. J. and Gruber, M. J. (2013), Mutual funds. *Handbook of the Economics of Finance* 2 (Part B), 1011-1061.
- Elton, E. J., Gruber, M. J., Blake, C. R., (2001), A first look at the accuracy of the CRSP mutual fund database and a comparison of the CRSP and Morningstar mutual fund databases, *Journal of Finance* 56(1), 2415–2430.
- Elton, E. J., Gruber, M. J., Das, S. and Hlavka, M. (1993), Efficiency with costly information: A reinterpretation of evidence from managed portfolios, *Review of Financial Studies* 6(1), 1–22.
- Fama, E. F. and French, K. R. (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33(1), 3–56.
- Fama, E. F. and French, K. R. (2010), Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65(5), 1915–1947.
- Fama, E. F. and French, K. R. (2015), A five-factor asset pricing model, *Journal of Financial Economics* 116(1), 1–22.
- Ferreira, M.A., Keswani, A., Miguel, A.F. and Ramos, S.B. (2012), The flow-performance relationship around the world, *Journal of Banking and Finance* 36(6), 1759–1780.
- Ferson, W. E. (2010), Investment performance evaluation. *Annual Review of Financial Economics*, 2, 207–234.
- Gallagher, D.R., Gardner, P.A., Schmidt, C.H. and Walter, T.S. (2014), Portfolio quality and mutual fund performance, *International Review of Finance* 14(4), 485–521.
- Gottesman, A. and Morey, M. (2007), Predicting emerging market mutual fund performance, *Journal of Investing* 16(3), 111–122.
- Gruber, M. (1996), Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51(3), 783– 810.

- Han, Y. and Lesmond, D. (2011), Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, *Review of Financial Studies* 24(5), 1590–1629.
- Hendricks, D., Patel, J. and Zeckhauser, R. (1993), Hot hands in mutual funds: Short-run persistence of performance, *Journal of Finance* 48(1), 93–130.
- Huang, W., Qianqiu, L. Rhee, S.G. and Zhang, L. (2010), Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies* 23(1), 147–168.
- Jagannathan, R. and Korajczyk, R. A. (1986), Assessing the market timing performance of managed portfolios, *Journal of Business* 59 (2), 217–235.
- Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48(1), 65–91.
- Jensen, M. (1968), The performance of mutual funds in the period 1945-1964, *Journal of Finance* 23(2), 389–416.
- Jordan, B.D. and Riley, T.B. (2015), Volatility and mutual fund manager skill, *Journal of Financial Economics* 118(2), 289–298.
- Malagón, J., Moreno, D. and Rodríguez, R. (2015), Time horizon trading and the idiosyncratic risk puzzle, *Quantitative Finance* 15(2), 327–343.
- Matallín-Sáez, J. C., Moreno, D. and Rodríguez, R. (2015), Why is timing perverse?, *European Journal of Finance* 21(15), 1334–1356.
- Newey, W. and West, K. (1987), A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55(3), 703–708.
- Pástor, L. and Stambaugh, R. (2002), Mutual fund performance and seemingly unrelated assets, *Journal of Financial Economics* 63(3), 315–349.
- Phalippou, L. (2014), Performance of buyout funds revisited?, *Review of Finance* 18(1), 189–218.
- Phillips, B., Pukthuanthong, K. and Rau, P.R. (2016), Past performance may be an illusion: Performance, flows, and fees in mutual funds. *Critical Finance Review* 5(2), 351–398.
- Sapp, T. and Tiwari, A. (2004), Does stock return momentum explain the “smart money” effect?, *Journal of Finance* 59(6), 2605–2622.
- Schneider, P., Wagner, C. and Zechner, J. (2020), Low-Risk Anomalies? *Journal of Finance* 75(5), 2673–2718.
- Sharpe, W. (1992), Asset allocation: Management style and performance measurement, *Journal of Portfolio Management* 18(1), 7–19.

- Shawky, H.A. and Smith, D.M. (2005), Optimal number of stock holdings in mutual fund portfolios based on market performance, *Financial Review* 40, 481–495.
- Sheng, J. and Simutin, M. and Zhang, T. (2019), Cheaper is not better: On the superior performance of high-fee mutual funds, *Rotman School of Management WP No.* 2912511.
- Teo, M. and Woo, S. (2004), Style effects in the cross-section of stock returns, *Journal of Financial Economics* 74(2), 367–398.
- Zheng, Lu (1999), Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54(3), 901– 933.

Table 1. Performance of quintile portfolios based on past (previous two years) R^2 of mutual funds

| | Low | Q2 | Q3 | Q4 | High | Low-High |
|-----------------|---------|---------|---------|---------|---------|----------|
| R^2 (%) | 97.0 | 98.2 | 98.6 | 99.1 | 99.6 | 65.6 |
| Performance (%) | -0.37 | -0.69 | -1.51 | -1.91 | -1.77 | 1.40 |
| | (0.550) | (0.209) | (0.003) | (0.000) | (0.000) | (0.038) |

Description: This table reports the R^2 and the annualized performance (both expressed as percentages) of portfolios that invest following a strategy based on past R^2 of mutual funds in the sample. Following Algorithm I, performance model 4F is applied to mutual funds and daily factor returns from the previous two years. Mutual funds are grouped in quintiles based on past R^2 . Portfolio *Low* consists of equally-weighted investing, over the next month, in the mutual funds with the lowest R^2 from the previous two years. The same pattern is followed by the rest of the portfolios up to *High*, which invests in the quintile of mutual funds with the highest R^2 in the previous two years. This procedure is repeated at the beginning of each month and daily returns are computed. Then the performance of the quintile portfolios and of the *Low* minus *High* portfolio is estimated by means of 4F model. The p -value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Interpretation: This table shows how the abnormal performance decreases monotonically across quintile portfolios as past R^2 increases. In fact, the difference between the performance of the *Low* and *High* quintile is 1.40% and significant. These results confirm evidence from Amihud and Goyenko (2013), i.e. an inverse relation between past mutual funds' R^2 and future performance.

Table 2. Performance of quintile portfolios based on past (previous two years) R^2 of types of stocks

| | Low | Q2 | Q3 | Q4 | High | Low-High |
|-----------------|---------|---------|---------|---------|---------|----------|
| R^2 (%) | 31.0 | 60.5 | 91.2 | 97.0 | 96.6 | 87.4 |
| Performance (%) | 37.01 | 24.51 | 11.03 | 5.21 | 2.42 | 34.60 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.024) | (0.000) |

Description: This table reports the R^2 and the annualized performance (both expressed as percentages) of portfolios that invest following a strategy based on past R^2 of the *Stocks* investment set in the sample. Following Algorithm I, performance model 4F is applied to stocks and daily factor returns from the previous two years. Stocks are grouped in quintiles based on past R^2 . Portfolio *Low* consists of equally-weighted investing, over the next month, in the stocks with the lowest R^2 from the previous two years. The same pattern is followed by the rest of the portfolios up to *High*, which invests in the quintile of stocks with the highest R^2 in the previous two years. This procedure is repeated at the beginning of each month and daily returns are computed. Then the performance of the quintile portfolios and of the *Low* minus *High* portfolio is estimated by means of 4F model. The p -value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Interpretation: This table shows how the abnormal performance decreases monotonically across quintile portfolios as past R^2 increases. This result has exactly the same abnormal rate of return patterns as those from mutual funds in Table 1. However, unlike mutual funds, stocks are not professionally managed, i.e. they are artificial investments; therefore the relationship between past R^2 risk and performance is not attributable to any active management.

Table 3. Performance of quintile portfolios based on past (previous two years) R^2 of mutual funds incorporating the additional ImS (Idiosyncratic minus systematic) factor in performance model

| | Low | Q2 | Q3 | Q4 | High | Low-High |
|-----------------|---------|---------|---------|---------|---------|----------|
| R^2 (%) | 97.3 | 98.2 | 98.7 | 99.2 | 99.6 | 69.0 |
| Performance (%) | -2.59 | -0.49 | 0.92 | 1.47 | -0.02 | -2.57 |
| | (0.003) | (0.530) | (0.215) | (0.013) | (0.966) | (0.001) |

Description: This table reports the R^2 and the annualized performance (both expressed as percentages) of portfolios that invest following a strategy based on past R^2 of mutual funds in the sample. In Algorithm I, an extended version of the performance model 4F including additionally the ImS factor, is applied to mutual funds and daily factor returns from the previous two years. The ImS factor captures the relationship between the percentage of past idiosyncratic risk and performance, and is defined as the return of the *Low-High* quintile portfolio provided for implementing Algorithm I for the *Stocks* investment set. Mutual funds are grouped in quintiles based on past R^2 . Portfolio *Low* consists of equally-weighted investing, over the next month, in the mutual funds with the lowest R^2 from the previous two years. The same pattern is followed by the rest of the portfolios up to *High*, which invests in the quintile of mutual funds with the highest R^2 in the previous two years. This procedure is repeated at the beginning of each month and daily returns are computed. Then the performance of the quintile portfolios and of the *Low* minus *High* portfolio is estimated by means of the extended version of the 4F model. The p -value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Interpretation: This table shows how after incorporating ImS factor, the inverse relationship between past R^2 and abnormal performance found in Table 1 for mutual funds vanishes.

Table 4. Performance (%) of *Low-High* quintile portfolios based on past (previous two years) R^2

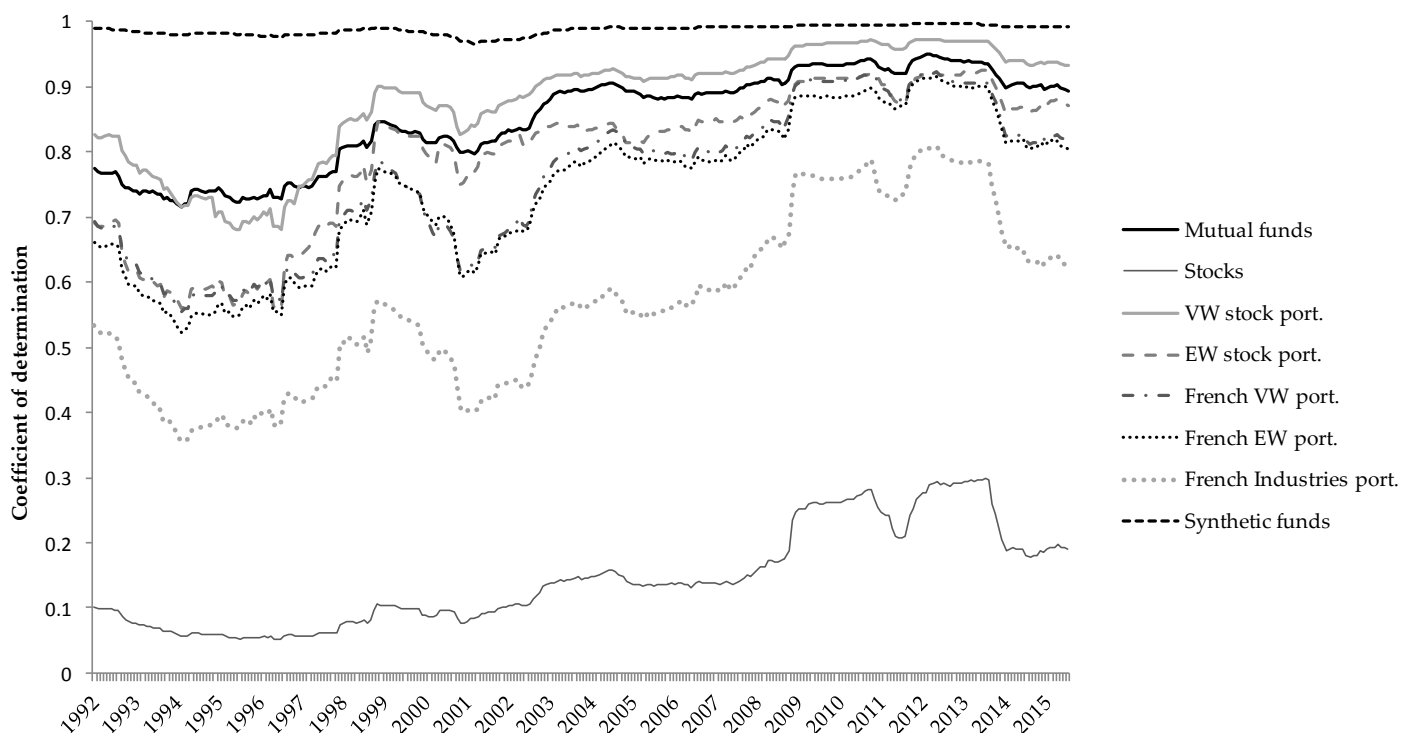
| Panel A. Sample 1990-06/2015 | | | | | | | | |
|---------------------------------|---------------------|------------------|----------------------------|----------------------------|-----------------------------|-----------------------------|-------------------------------------|------------------------|
| Model | (1) Mutual funds | (2) Stocks | (3) VW stock portfolios | (4) EW stock portfolios | (5) French VW portfolios | (6) French EW portfolios | (7) French Industries portfolios | (8) Synthetic funds |
| 4F | 1.40 (0.038) | 34.60 (0.000) | 1.97 (0.000) | 4.92 (0.000) | 3.49 (0.002) | 11.73 (0.000) | 2.53 (0.207) | 3.58 (0.000) |
| 5F | 1.57 (0.017) | 36.17 (0.000) | 1.95 (0.000) | 5.07 (0.000) | 3.83 (0.000) | 12.41 (0.000) | 0.48 (0.797) | 3.70 (0.000) |
| 7F | 1.63 (0.006) | 34.79 (0.000) | 2.04 (0.000) | 5.05 (0.000) | 3.91 (0.000) | 12.02 (0.000) | 0.10 (0.616) | 4.64 (0.000) |
| Panel B. Subsample 1990-1997 | | | | | | | | |
| 4F | 2.45 (0.002) | 40.65 (0.000) | 1.52 (0.000) | 5.03 (0.000) | 4.45 (0.000) | 22.63 (0.000) | 8.78 (0.001) | 4.38 (0.000) |
| 5F | 2.50 (0.001) | 39.13 (0.000) | 1.69 (0.000) | 4.99 (0.000) | 4.43 (0.000) | 22.10 (0.000) | 6.76 (0.007) | 6.24 (0.000) |
| 7F | 1.93 (0.012) | 34.13 (0.000) | 1.45 (0.000) | 4.66 (0.000) | 2.74 (0.001) | 19.83 (0.000) | 5.84 (0.022) | 6.13 (0.000) |
| Panel C. Subsample 1998-2007 | | | | | | | | |
| 4F | 2.86 (0.003) | 29.78 (0.000) | 1.89 (0.000) | 4.63 (0.000) | 4.01 (0.016) | 9.14 (0.000) | 0.53 (0.869) | 3.41 (0.001) |
| 5F | 3.22 (0.001) | 32.58 (0.000) | 2.03 (0.000) | 4.86 (0.000) | 5.22 (0.001) | 10.96 (0.000) | 1.19 (0.699) | 3.50 (0.000) |
| 7F | 3.39 (0.000) | 29.35 (0.000) | 1.91 (0.000) | 4.71 (0.000) | 4.94 (0.001) | 9.60 (0.000) | -0.39 (0.907) | 4.62 (0.000) |
| Panel D. Subsample 2008-06/2015 | | | | | | | | |
| 4F | -1.49 (0.160) | 31.90 (0.000) | 1.89 (0.000) | 4.90 (0.000) | 0.93 (0.582) | 5.46 (0.024) | -0.61 (0.846) | 1.99 (0.017) |
| 5F | -0.85 (0.372) | 33.37 (0.000) | 2.46 (0.000) | 5.24 (0.000) | 2.57 (0.090) | 7.35 (0.001) | -2.85 (0.348) | 3.14 (0.001) |
| 7F | -2.00 (0.021) | 31.80 (0.000) | 1.20 (0.000) | 5.05 (0.000) | -0.66 (0.631) | 4.88 (0.037) | -2.72 (0.376) | 2.16 (0.003) |

Description: This table reports the difference between the annualized performances (expressed as a percentage) of the *Low* and *High* quintile portfolios that invest following a strategy based on past R^2 of different sets of investments. In the first column and following Algorithm I, performance models 4F, 5F and 7F are applied to mutual funds and daily factor returns from the previous two years. Mutual funds are grouped in quintiles based on past R^2 . Portfolio *Low* (*High*) consists of equally-weighted investing, over the next month, in the mutual funds with the lowest (highest) R^2 from the previous two years. This procedure is repeated at the beginning of each month and daily returns are computed. Then the performance of the quintile portfolios is estimated by means of 4F, 5F and 7F models, respectively. For the next columns, this procedure is repeated for other investments. *Stocks* are the equities traded on the NYSE, AMEX and NASDAQ stock markets. From these stocks are formed the randomly and value (equally) weighted *VW* and *EW stock portfolios*. *French VW* and *EW portfolios* are, respectively, two sets of 300 value and (equally) weighted artificial portfolios from French's data library formed by sorting stocks according to size, book-to-market, operating profitability and investment. *French Industries portfolios* is a set of 98 equally and value weighted

artificial portfolios, also from French's data library, formed by sorting stocks according to their industrial sector. Finally, *Synthetic funds* is a set of artificial portfolios estimated by solving the linear problem (2)-(5). The p -value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Interpretation: According to column (1), the evidence found in Table 1 for mutual funds is robust to the performance model considered, 4F, 5F and 7F. The inverse relationship between past R^2 and abnormal performance found for mutual funds does not hold for the most recent sample subperiod, January 2008 to June 2015. On the other hand, columns (2) to (8) show, in general, an inverse relation between past R^2 and future performance for different sets of artificial portfolios that is not attributable to any professional active management. It is therefore possible that a higher level of past active management does not imply superior performance as Amihud and Goyenko (2013) pointed out, but to some extent this could be an implicit effect of the stocks in which the fund invests, as was found for the case of artificial portfolios.

Figure 1. The time pattern of R^2 for active and artificial investments



Description: This figure reports average values of the R^2 for each set of investments through the application of the 4F model in Algorithm I, using daily returns and a two-year rolling window. *Mutual funds* is a set of 4,467 US domestic equity mutual funds. *Stocks* are the equities traded on the NYSE, AMEX and NASDAQ stock markets. From these stocks are formed the randomly and value (equally) weighted *VW* and *EW stock portfolios*. *French VW* and *EW portfolios* are respectively two sets of 300 value and (equally) weighted artificial portfolios from French's data library formed by sorting stocks according to size, book-to-market, operating profitability and investment. *French Industries portfolios* is a set of 98 equally and value weighted artificial portfolios, also from French's data library, formed by sorting stocks according to their industrial sector. Finally, *Synthetic funds* is a set of artificial portfolios estimated by solving the linear problem (2)-(5).

Interpretation: The figure shows how the time pattern of the R^2 of mutual funds is similar to that shown by stocks and artificial portfolios. Especially for the set of the *VW stock portfolios*, both the level of R^2 and its behavior over time is very similar to that shown by mutual funds. Therefore it would be reasonable to think that the percentage of idiosyncratic risk of the mutual funds would be driven mainly by the percentage of idiosyncratic risk of the underlying stocks rather than active management and in this case, the relationship between past R^2 and performance would be an implicit result and not due to managers' ability.