Online Appendix

Better performance of mutual funds with lower R^2's

does not suggest that active management pays

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December 8, 2020

* 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.

1. Methodology

1.1 Estimating synthetic funds

We compare the results achieved by applying Algorithm I for the mutual funds sample with those obtained with the same algorithm for synthetic artificial portfolios which mimic the style of the mutual funds. This approach of building portfolios by mimicking style, or simulating strategies, has been documented in previous literature such as Bollen and Busse (2001 and 2005), Benos and Jochec (2011) and Matallín-Sáez et al. (2016), among others. Comparing mutual fund behavior with synthetic counterparts is a useful nonparametric procedure for assessing mutual funds because it attempts to avoid the artificial or passive effects found when estimating performance models as we note in Appendix 1. To form synthetic funds, we applied the methodology proposed by Sharpe (1992), estimating the weight $w_{Sp,b}$ invested (subject to conditions of non-negativity and convexity) in each benchmark b (for b=1 to B benchmarks)1 that solve the linear programming problem defined by equations (2)-(5).

$$r_{Sp,t} = \sum_{b=1}^{B} w_{Sp,b} r_{b,t} \tag{2}$$

$$\varepsilon_{Sp,t} = r_{p,t} - r_{Sp,t} \tag{3}$$

$$\text{Minimize } \sum_{t=1}^{T} \varepsilon_{Sp,t}^{2} \tag{4}$$

$$\text{Subject to: } w_{Sp,b} \geq 0 \text{ and } \sum_{b=1}^{B} w_{Sp,b} = 1 \tag{5}$$

Therefore, for each p mutual fund in the sample we construct a synthetic fund S_p that mimics its style. What is relevant is that the synthetic funds are artificial by definition so any relationship between the percentage of idiosyncratic risk and performance will not be attributable to professional active management, but to the behavior of the underlying assets that define the style of the fund. This procedure therefore improves the comparability of the results of Algorithm I for mutual funds and those for artificial portfolios, because the latter are synthetic and will be close to their mutual fund counterparts.

[1] We consider 36 equally and value weighted benchmarks which combine different styles or stock characteristics, namely *size* and *book-to-market*, *operating profitability* and *investment*. Weights are fixed because synthetic funds follow a passive "buy and hold" strategy in the benchmarks.

2. Data
2.1 Descriptive statistics

Table W1 provides some statistics for the mutual funds and factors in the sample. Panel A shows different behavior across styles. On average and related to size, Large and Index funds achieve lower return and risk. In contrast, Mid and Small style groups show higher levels of return and risk and are more expensive. Related to book-to-market ratio, growth funds are more risky and expensive than funds from blend and value styles.

Panel B of Table W1 shows some descriptive statistics for factors used in the performance models. First, note that there are important differences between the return and risk of the factors. Related to the sample subperiod considered, the market factor column shows that the first subperiod, 1990–1997, has the best risk-return performance. The other two subperiods are characterized by higher risk, 1998-2007 showing the lowest mean return.

Table W2 presents a summary statistics for artificial investments: French's VW, EW and Industries portfolios: the average return (mean) and risk (s.d.). The last column on the right shows the average for all 300 portfolios. Panel A shows the data for the case of the value-weighted stocks in the portfolios, *French VW portfolios*, and Panel B when the stocks are equally-weighted, *French EW portfolios*. Moreover, for exhibition purposes, the rest of the columns show the averages when in each panel the 300 portfolios are grouped in deciles according their size. A comparison of the 'all portfolios' column of the two panels shows that risk levels are similar but average return is higher in equally-weighted portfolios, particularly for the first subperiod 1990-1997. Considering deciles and the whole sample period, the average return of equally-weighted portfolios is, in general, higher than that of value-weighted portfolios. The size effect is especially relevant for the smallest stocks in decile D1, where average return was 13.18% in Panel A, but 32.51% for the equally-weighted case in Panel B. This effect occurs most intensely in the first subperiod.

Panel B of Table W3 shows some descriptive statistics of the sets of artificial investments: *Stocks*, *VW* and *EW stock portfolios*. As in Table W2, the equally weighted portfolios in Table W3 show better performance. In addition, the mean return continues to decrease over time through the subperiods considered.

Table W4 shows some descriptive statistics of the benchmarks used for estimating synthetic funds. Stocks in the portfolios were value-weighted in Panel A and equally-weighted in Panel B. The first rows in the panels (for the whole period sample) reveal that in some cases the equally-weighted portfolios have a higher risk than the value-weighted case, but in other cases the opposite occurs, especially for the case of small style portfolios. However, in these first rows, the return of equally-weighted portfolios is higher in Panel B than in Panel A in all cases. The effect of equally weighting is higher for the case of small style portfolios in Panel B, for which the mean return is two or three times higher than in Panel A. Similarly to Tables W2 and W3, the data in Table W4 shows the best performance in general for equally-weighted portfolios.

2.2 Synthetic artificial fund estimation

We also analyze the predictive capacity of R^2 for a seventh set of artificial portfolios, namely synthetic funds that mimic the style of the mutual funds in the sample. For this purpose, we solve the linear programming problem defined by equations (2)-(5). First, we define a large enough number of benchmarks (B = 36) to ensure a wide range of styles and thus avoid omitted benchmark bias (Elton et al., 1993; Pástor and Stambaugh, 2002; Phalippou 2014), but sufficiently limited to effectively develop the optimization procedure. We use the Fama-French Research Portfolios from French's data library. The first 6 portfolios combine 2x3 *size* and *book-to-market* characteristics, the next 6 combine 2x3 *size* and *operating profitability* and finally, 2x3 portfolios combine *size* and *investment*. There are 18 benchmarks in total, but in light of the relevant differences when we compared value-weighted and equally-weighted stocks, we also consider the two cases here, therefore yielding 36 benchmarks. Thus, by using a high number of benchmarks and not restricting weighting type, we provide more freedom in the optimization of the problem defined by (2)-(5) to more easily achieve the combination that best represents the style of the fund.

Next, we solve the linear programming problem (2)–(5) for each mutual fund in the sample to estimate its synthetic counterpart fund. The aim is to find a synthetic artificial fund that replicates the average style of each mutual fund. Table W5 shows some summary statistics for the estimated synthetic funds. The mean of the correlation coefficient between the returns of each mutual fund and its counterpart synthetic fund is 0.923 for all the funds; the largest being for the *Index* style funds (0.9537) and the lowest for the *Mid-Cap Blend* style (0.8978). In general correlations are higher, meaning that a significant percentage of the behavior of the mutual funds can be explained by their style.[2]

3. Results

3.1 Additional comments on results shown in the main document

3.1.1 Considering artificial investments

Column (2) of Table 4 in the main paper shows the results for the set of *Stocks*. Unlike in the mutual funds case, Algorithm I is applied for stocks instead of for portfolios formed by stocks. When forming portfolios, the idiosyncratic risk of the stocks is weighted, thus averaging the greater or lesser idiosyncratic risk of stocks in the portfolio. On the other hand, diversification reduces the contribution of this risk to the total risk of the portfolio. Therefore, idiosyncratic risk tends to be more relevant for stocks than for portfolios. If there is a positive relationship between this risk and future performance (i.e. an inverse relationship between R^2 and performance), this relationship would be more evident when applying Algorithm I directly for stocks than for the portfolios. Thus, the algorithm will be more efficient when the investments, in this case stocks, with the lowest (highest) past R^2 are included in the *Low* (*High*) quintile portfolio. Column (2) of Table 4 shows how, effectively, the differences between the annualized abnormal performance of the *Low* and *High* quintile take higher and significant values in all subperiods and models. For instance, in Panel A and for the 4F model the difference is an annualized 34.6%. Therefore, a positive relationship between the percentage of past idiosyncratic risk of stocks and performance is found, in line with the studies of Goyal and Santa-Clara (2003), Wei and Zhang (2005) and Fu (2009), among others[3].

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[2] The problem (2)-(5) was also solved considering only the 18 Fama-French Research Portfolios, value- or equally-weighted. The results were similar, but in both cases the correlation mean between mutual funds and their synthetic counterparts was lower. Concretely, when value- and equally-weighted benchmarks were used jointly, the average of the correlation was 0.24% (1.94%) higher than the case in which only the value-(equally-) weighted benchmarks were used; and grouping mutual funds by styles, in all the cases the correlation was higher with more intensity for small and mid-cap (large and index) styles.

[3] Different theoretical arguments have been put forward, so while standard asset pricing models propose that only systematic risks should be priced, Merton (1987) argues that idiosyncratic risk should be rewarded if investors cannot diversify their portfolios. Ang et al. (2006) found a negative relation between idiosyncratic risk and stock returns. In

It is interesting to analyze the behavior of the inverse relationship between past R^2 and performance when stocks are introduced into portfolios. As we have already pointed out, in the portfolio idiosyncratic risk is weighted and its relevance reduced by diversification, and therefore this relationship should be less strong than for the case of individual stocks. With this purpose, we generate the second and third sets of artificial portfolios, which invest randomly in the stock sample, following a buy-and-hold strategy. Also to compare with the case of mutual funds, the number of portfolios created is the same as that of mutual funds. Thus, 4,467 value weighted portfolios are created, *VW stock portfolios*, and the same number of equally weighted portfolios, *EW stock portfolios*. Next, Algorithm I is applied in the same way as in the previous cases; the results are displayed in columns (3) and (4) of Table 4 in the main paper. As noted, for all models and subperiods the differences between the annualized abnormal performance of the *Low* and *High* quintile are positive and significant, i.e., a negative (positive) relationship is found between past R^2 (percentage of idiosyncratic risk) and performance. These differences are higher for the EW case in column (4) than for the VW case, i.e., this relationship is stronger for the smallest stocks. It is also observed that except for Panel D for the last subperiod, the values taken by column (3) corresponding to *VW stock portfolios* are the closest to the values taken by the mutual funds in column (1).

We also apply Algorithm I for portfolios formed according to financial characteristics. The next columns in Table 4 show the results for two sets of 300 Fama-French Research Portfolios from French's data library. Column (5) shows the results for *French VW portfolios* in which stocks are value weighted. The differences between *Low* and *High* quintiles are positive and significant. However, for the most recent sample subperiod, January 2008 to June 2015 in Panel D, the difference is lower and, depending on the model considered, a lack of significance is found. This pattern is similar to that found for the mutual funds case. Column (6) shows the results for the set of *French EW portfolios*, in which stocks were equally weighted. Comparing with the results for the

contrast, Fu (2009) shows that idiosyncratic volatilities are time-varying and finds a positive relation. Some studies present evidence of how the sign of this relation depends on the sample period. Goyal and Santa-Clara (2003) find a positive relation, but Bali et al. (2005) argue that this evidence is driven by the liquidity premium of some small stocks and the period sample considered; in this same line, Wei and Zhang (2005) also find that the positive relation is mainly driven by the data in the 1990s. Most of the recent literature provides varying explanations for this puzzle; see Chen and Petkova (2012) and Babenko et al. (2016), among others.

VW case, the differences between the performance of the *Low* and *High* quintile portfolios are higher and more significant. As in our comparison of columns (3) and (4), the relationship between past R^2 and performance is stronger for the smallest stocks. In subsection 3.1.5 we will analyze the role stock size plays in this issue.

The sixth set of artificial investments is made up of 98 *French Industries portfolios*. Column (7) of Table 4, in the main paper, displays the results. For the whole sample period, the differences between the performance of the *Low* and *High* quintile portfolios are positive but not significant. In Panel B, for the first subperiod, the differences are positive and significant. For the other subperiods, the difference is not significant and is even negative for the third period, in line with the results for mutual funds in column (1). It seems that the relationship between past R^2 and future performance at the level of stocks is characterized mainly by size and other characteristics usually used in asset pricing models. However, the transversal nature of the industrial sector groups stocks with different characteristics and it dilutes the evidence about this relationship. In fact, the industrial sector is not usually considered as an explanatory factor in the commonly used pricing models.

Finally, we create a seventh set of artificial portfolios, named synthetic funds, which replicate the style of the mutual funds in the sample. With this aim, we solve the linear programming problem (2)–(5) for each mutual fund, thus creating a synthetic counterpart close to the assessed mutual fund but lacking professional active management. Then, by comparing the synthetic and active mutual funds we can measure the performance, from an investment strategy based on past R^2, which is attributable to an artificial or active effect from the percentage of idiosyncratic risk. Then, for each model 4F, 5F and 7F, Algorithm I is applied for the set of synthetic funds. Column (8) in Table 4 shows a positive relation between the percentage of past idiosyncratic risk and performance not attributable to any active management.

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

Table W6 reports the correlations between the R^2 of mutual funds and different artificial investments. We again applied models 4F, 5F and 7F in Algorithm I 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. 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.

Next, we analyze whether the previous aggregated results hold for the case of investments with lower (higher) values of R^2, because the difference in the performance of the *Low* and *High* past R^2 quintiles is the core issue of our study. For instance, in the fifth column of Panel B and model 4F, the correlation between the mutual funds' R^2 with the lowest R^2 and those corresponding to the *VW stock portfolios*, also with the lowest R^2, is a significant 0.916. From this result it follows that 83.9% of the R^2 of the mutual funds in the *Low* R^2 quintile portfolio is explained by the *VW stock portfolios* also with lower R^2. The results in Panel C for investments with higher R^2 are very similar.

3.1.3 The time pattern of the performance linked to past R^2 of mutual funds and artificial portfolios

In the previous subsection we showed how a high percentage of the evolution of R^2 in mutual funds is common to that experienced by artificial investments. Therefore, part of this evolution would be due to the underlying assets of the fund and not to the managers. On the other hand, in general and at an aggregate level, a positive (inverse) relation between the percentage of past idiosyncratic risk (R^2) and performance was found, both for the mutual funds and for artificial investments. It is therefore interesting to analyze whether this performance also has a common behavior. This would help us to further identify to what extent the performance obtained by following a strategy based on past R^2 is due to the active management of the portfolio or, on the contrary, to the artificial behavior of the underlying stocks. This procedure is a robustness analysis for the results shown in Table 3 in section 4.1 of the main paper. It included *ImS* as an additional factor to explain the returns on mutual funds and quintile portfolios. As an alternative, we will now explain the time pattern of the abnormal performance instead of the returns. To this end we applied models 4F, 5F and 7F using a non-overlapping 2-month rolling window over daily returns of quintile portfolios formed following Algorithm I. The time series of the performance of artificial quintile portfolios are correlated and therefore they are orthogonalized with respect to the quintile portfolios of *Synthetic funds* since these are the ones with the highest explained variance.

The results are shown in Table W7. Firstly, for the mutual funds' *Low* quintile portfolio—that is, with lower R^2 —the intercept is negative and significant in all the models, taking an annualized value of -3.93% for the 4F model. The parameters corresponding to the *French VW portfolios* and the *Synthetic funds* are positive and significant. The time changes of performance are explained in the 4F model by 46% of the evolution of the abnormal performance in artificial portfolios. For the quintile portfolio *High*, the relationship with artificial portfolios is lower, so with the 4F model the percentage explained is only 12%. The intercept remains negative and significant. That is, for high R^2 the performance obtained by mutual funds differs much more than that obtained by the artificial portfolios, possibly due to the lower percentage of idiosyncratic risk. Finally, the last columns show the results for the *Low-High* portfolio quintile. The results are similar to those obtained for the *High* quintile portfolio, so with the 4F model, 53% of the time variation of the fund's performance is explained artificially. This evidence elicits two comments: first, that the performance achieved by mutual funds' 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, 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 Tables 3 and 4 in the main paper).

As we point out in Appendix 2, a mutual fund's idiosyncratic risk is caused by two components: first, the active management, and second, the passive idiosyncratic risk from underlying assets. However, for an artificial portfolio, only this second component is present. As we pointed out, the percentage of idiosyncratic risk of mutual funds would be significantly explained by the percentage of idiosyncratic risk of artificial investments. Then it is feasible to consider that the rest of the idiosyncratic risk in mutual funds is due to active management. Results from Tables 2 and 4 indicate that for artificial portfolios, investment strategies based on past R^2 perform similarly or better than for mutual funds. Thus, the fact that performance for the case of the two components of idiosyncratic risk is worse or similar when only the second is present would evidence that for the set of mutual funds, the first component, i.e., that linked to the active management, has a negative or non-significant effect on mutual fund performance. In line with previous evidence from the financial literature, (Carhart 1997, Elton and Gruber, 2013; Ferreira et al., 2012 among others) this result does not support the existence of skilled or informed mutual fund managers, from the perspective of investors[4].

3.1.4 Performance of quintile portfolios based on past mutual funds' R^2 grouped by style

In this section 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. To this end, mutual funds are grouped according to their style. Table W1 showed information on the number of funds in each style. Separately, within each group of funds we apply Algorithm I. This procedure is repeated for each performance model and for each subsample period. Finally the performance of each quintile portfolio is obtained. Table W8 shows the difference between the performance of *Low* and *High* quintile portfolios and their significance.

Table W8 reveals that, in general, for the whole of the sample period only small value, mid-cap blend and large growth styles show positive and significant performance. For the first subperiod, from 1990 to 1997, only mid-cap blend and large growth, and mid-cap growth perform positively and significantly, depending on the performance model. For the 1998-2007 subperiod the evidence of positive performance is higher. For instance, for the small value style the performance ranges from an annualized 5.06% (4F model) to 5.56% (5F and 7F models). In general, performance is also positive and significant for the rest of styles except for mid-cap growth, mid-cap value and index styles. In the last subperiod, 2008 to 2015, the performance is negative and significant for small growth, mid-cap growth and for mid-cap blend with the 4F model case. In short, as we noted in comments on Table 4, our findings evidence that the inverse relationship between past R^2 and performance is an empirical fact that does not persist over time. Moreover, 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.

[4] Although it is appropriate to clarify that no trading costs for artificial investments or sales charges and load fees for mutual funds have been considered.

3.1.5 Performance of quintile portfolios based on past artificial portfolios' R^2 grouped by size

In this subsection the *French VW* and *EW* artificial portfolios previously described are grouped in deciles according to the size of their stocks. Hence the *Low* (*High*) size decile is formed by the 30 portfolios with stocks of a lower (higher) size. Algorithm I is then applied within each size decile separately for different performance models and subsample periods. Table W9 shows the difference between the performance of *Low* and *High* quintile portfolios within each size decile. Panel A of Table W9 and Figures W1.a, W1.b and W1.c show the results when stocks are value-weighted. These figures show how the difference between the performance of *Low* and *High* quintile portfolios decreases as size increases, and for deciles of big stocks it even takes a negative value. Comparing models, the results of 4F and 5F seem closer to each other and show more variability depending on the period and size decile considered. Comparing subperiods, as we mentioned above, the differences in performance are higher in the first subperiod and smaller in the last one. Panel A of Table W9 shows how the differences are in general positive and significant only from *Low* to *D4* size deciles when the whole sample and first subperiod are considered and partially significant for the second subperiod. As in Panel D of Table 4, in general, for the last subperiod differences are not significant. For the rest of the size deciles the differences decrease and in general are not significant, and in some cases it is even negative for higher size deciles. For this evidence, note that the empirical best performance found for the stocks with lower past R^2 in Table W9 is only present when small and small-medium stocks are considered. In contrast, for medium and big stocks this evidence vanishes and lower past R^2 even implies worse future performance.

Panel B of Table W9 and Figures W1.d, W1.e and W1.f show the results when stocks are equally-weighted. The evidence is similar to that for Panel A when stocks were value-weighted. But the main difference is found for the *Low* size decile because the differences between the performance of *Low* and *High* past R^2 quintile portfolios are, in general, not significant and even negative in some cases. To explain this behavior, we consider, for instance, the case of the whole sample period and model 4F. In this case, the annualized performance of the quintile portfolios in the *Low* size decile are: 24.27%(*Low* past R^2), 24.14%(*Q2*), 23.26%(*Q3*), 23.05%(*Q4*) and 23.84%(*High* past

R^2), then the difference *Low* minus *High* is the 0.44% shown in the first cell at the top left of Panel B. These values show how 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 microcap[5] stocks which gain weight in the case of equal weighting. Then, the portfolios perform so well that past R^2 is not a distinctive characteristic within them. However, when small stocks are not restricted to a subset but included in a larger set along with the other stocks, then they are likely to become part of the quintile portfolios, thus enabling differences to exist in the performance of these portfolios. This behavior and the fact that small stocks gain weight in the 300 equally-weighted artificial portfolios explain the remarkable results of column (3) of Table 4. So even in the last subperiod the performance of the *Low-High* quintile portfolio is positive and significant.

In short, we find evidence that *French VW* and *EW* artificial portfolios with lower past R^2 show better performance in the next short-term period. When portfolios are grouped in deciles according to style size, 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.

3.1.6 Performance of quintile portfolios based on past synthetic funds' R^2 grouped by style

The synthetic funds are grouped according to their style. Separately, within each group of synthetic funds we again apply Algorithm I. This procedure is repeated for each performance model and for each subsample period. Finally the performance of each quintile portfolio is obtained. Table W10 shows the difference between the performance of *Low* and *High* quintile portfolios and their significance. The first columns on the left show the results for the whole sample period. In general, performance is positive and significant for all styles and models. Nevertheless there are differences in the values of the abnormal performance depending on style. Also, as in previous tables, we found differences depending on the subperiod considered, thus the poorest results are from the subperiod 2008-2015.

[5] 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.

3.1.7 Volatility, idiosyncratic volatility and R^2

As R^2 depends both on idiosyncratic volatility (s.e. regression) (IVOL) and on volatility (s.d. return) (VOL), we analyze the relationship between these variables in the context of the results of our study and the previous literature. In this section, to facilitate comparison we will refer to $1-R^2$, that is, the percentage of IVOL. First, for the whole of the sample period and applying the baseline model (4F) on daily returns, Table W11 shows the correlations between these variables, in Panel A for mutual funds and in Panel B for stocks.

The correlation between VOL and IVOL is positive, significant and high (0.815), which means that in general the funds with higher risk also show higher idiosyncratic risk. The correlation between VOL and $1-R^2$, although positive, takes a low value (0.179), meaning that ordering funds according to these variables can provide different results. In fact, it just allows that the results of Jordan and Riley (2015) and Amihud and Goyenko (2013) could differ. In the first of these studies, funds with higher past volatility perform worse, but in the last two, funds with higher past $1-R^2$ perform better.[6]

On the other hand, the correlation between IVOL and $1-R^2$ is positive and significant (0.602), which implies that an ordering of the funds would be fairly similar using either of these two variables. Amihud and Goyenko (2013) and our study find a positive relationship between past $1-R^2$ and performance. We also find the same 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 that high idiosyncratic volatility stocks perform worse.

In order to analyze this question, firstly Panel B of Table W11 shows the correlations discussed above but for the case of individual stocks. The correlation between VOL and IVOL is very high (0.997), due in part to the fact that the majority of stock risk is idiosyncratic. The correlation between IVOL and $1-R^2$, although positive, takes a lower value (0.315), so it is possible that there is a disparity in the ordering of stocks based on

[6] In Table 3 of Jordan and Riley (2015), the VOL for *Low* (*High*) funds according to past volatility is 1.00% (1.77%) and the IVOL is 0.27% (0.46%), respectively, so $1-R^2$ would be 27% (25.99%). In short, both *Low* and *High* VOL funds show similar $1-R^2$ values, and are even slightly higher for *Low*.

these variables, therefore leading to a different relationship with respect to future performance, which could reconcile our evidence with that of Ang, et al (2006).

In order to delve into this question, we analyzed the relationship between past IVOL and performance for the sample of stocks. The Fama and French (1993) three-factor model was applied on stock returns. Then stocks were ordered according to their IVOL, quintile portfolios were formed with monthly rebalancing, and finally, their performance was calculated. Our results show that high IVOL stocks perform better. This evidence is consistent with our results when ordering by $1-R^2$, but different from that of Ang et al. (2006).

In this vein, subsequent literature has identified some issues regarding the negative relation between IVOL and performance found by Ang et al. (2006). Bali and Cakici (2008) indicate that this relation is not robustly significant because it is driven by the value-weighted scheme forming portfolios, the small, illiquid stocks, the role of different breakpoints, and the data frequency. In the same line, Huang et al. (2010) show how when controlling for return reversals, the negative relation is no longer significant and they even find a positive relation when they use conditional IVOL. They also find that forming value weighted portfolios enhances the reversal effect and the negative relation. Han and Lesmond (2011) show that when controlling for the effect of liquidity on the estimation of IVOL, the relation is insignificant. Malagón et al. (2013) point out that the relationship only holds for short-term horizons. More recently, Schneider et al. (2020) show that the low-risk anomalies (which include the idiosyncratic volatility puzzle) reduce their magnitude and are insignificant when skewness factors are included in the asset pricing model. In relation to the sample period considered, Han and Lesmond (2011) find a decline in the pricing ability of IVOL from 1992.

Our discrepancies with Ang et al.'s (2006) study could therefore be due to the different periods considered, the weighting scheme, or sample screening. Although the results show some differences depending on these requirements, our evidence holds[7]. In line

[7] Firstly, as we compare artificial portfolios with mutual funds we used the total return (from prices and reinvestment of dividends) of the stocks. However, asset pricing studies usually use returns only from adjusted prices. We therefore formed a new database, again calculating the returns from these prices. Using these data, the results were similar to those previously achieved. Second, and following previous literature, we established different filters on the stock sample, such as selecting only a few markets among NYSE, NASDAQ and AMEX, or removing penny stocks

with Bali and Cakici (2008), we find that our results are mainly driven by the performance of the high IVOL quintile and that it contains much smaller stocks. As we have pointed out throughout our study, the negative relationship between past R^2 and performance is stronger for the smallest stocks. Similarly, Bali and Cakici (2005) show that the evidence of a positive relationship between volatility and returns found by Goyal and Santa-Clara (2003) is driven by small stocks. Therefore, it seems that small stocks play a relevant role in explaining the relationship between IVOL or $1-R^2$ and performance, whether it has a negative or a positive sign. In this sense, it is reasonable that big and mid cap stocks will be considered in any sample; however different screens or data sources may affect the selection of small and micro cap stocks. Therefore, given the sensitivity of the results to these types of assets, different evidence could be found with different samples. We address this question in the next section.

3.1.8 Database robustness analysis

The studies referred to in the previous section (Ang et al. 2006, Bali and Cakici 2008, Huang et al. 2010, Han and Lesmond 2011, Malagón et al. 2013 and Schneider et al. 2020) use the CRSP database, usually common stocks with share codes 10 and 11. In our study we form the sample with common stocks of NYSE / AMEX / NASDAQ from the Morningstar database. We compared the two databases and they include different firms. Specifically, Morningstar includes 44.73% of the stocks in CRSP, and the CRSP includes 35.78% of the stocks in Morningstar. To assess the robustness of the sample and our results, we use portfolio holdings data of mutual funds. From this information we perform two analyses, the first at an aggregate level and the second at an individual level for a subsample of mutual funds.

In the aggregate-level analysis, first we use the data of the monthly percentages of asset allocation in each of the nine categories in the Morningstar Style-box. This percentage is produced by Morningstar from the data of individual portfolio holdings. Then we compute the mean of these data for each fund. The first row of Panel A of Table W12 shows the average for all funds and the whole sample period in each style. The sum of these values is 92.88%, the rest being liquidity and the investment in other assets. Funds

(price under \$ 5.00) and micro caps (size under \$ 300 million). Although the results differ quantitatively, they are in line with our previous evidence.

are ordered by their average quintile according to their past R^2 using the 4F model. Then, quartiles are formed from lowest to highest average. The results are shown in the next rows of Panel A, and show how funds with lower R^2 invest more (less) in small (large) stocks than the funds with higher R^2.

Next, Panel B shows the results for the stocks. Firstly, the weight of each style in the market is shown in the first row. When compared with the first row of panel A, it appears that mutual funds on average, likely due to diversification and active management, overweight (underweight) small (large) stocks with respect to their market value. Secondly, if, as we propose in our study, the relationship between past R^2 and performance is driven by the stocks in which the fund invests, then stocks with lower (higher) R^2 will, in general, also be classified as small (large) styles. Therefore, in a similar way to funds, we have formed portfolio quartiles that group stocks according to the average quintile by past R^2 using the 4F model. Then the mean weight in each stock style is calculated for the portfolio quartile. The results of Panel B of Table W12 confirm our hypothesis. Thus, for the quartile of stocks with low (high) R^2, the investment in the small (large) styles is higher and it is nonexistent (reduced) in the large (small) styles. Therefore, considering the information from the funds' holdings and ordering by R^2, we observe that the asset allocation of mutual funds is consistent with that found for the stocks in our sample. In this regard, Panel C shows the results of regressing the differences in asset allocation of the mutual funds on those same differences for stocks. We found that stocks show capacity to explain the asset allocation of the mutual funds according to R^2, the slope being positive and significant in both cases.

Secondly, to analyze the robustness of the sample of stocks, we propose an individual analysis for a subsample of mutual funds. Using the average of quintiles, we select the five funds with the lowest (highest) past R^2 and highest (lowest) performance according to the 4F model within the *small value* style. This style was selected because it shows the best performance for the *Low-High* quintile portfolio based on past R^2 (see Table W8). For these funds and the whole sample period, we obtain data, usually quarterly, of their portfolio holdings. Next, we compare the stocks in the holdings with those in both the Morningstar and the CRSP databases. Panel A of Table W13 shows the weight of the holdings corresponding to the stocks included in these databases and separated by markets. In aggregate and for the *Low* R^2 funds of this subsample, Morningstar covers 78.01% of their portfolio holdings and CRSP, 47.18%. For the sub-sample of *High* R^2 funds, the weight covered is 86.32% and 42.67%, respectively. Regarding the markets, the largest differences between the two databases are for NASDAQ.

Unlike studies on the framework of asset pricing models such as those cited above (Ang et al., 2006, among others), this paper focuses on the mutual funds industry. Although we are aware of the limited subsample of funds analyzed in this subsection, we find that the universe of stocks in which the funds invest is larger than that covered by the common stocks in the Morningstar and CRSP databases. Especially in the latter case, the differences with respect to the mutual funds are remarkable. As we pointed out in section 3.2.7, it is most likely that the differences in the databases are due to the smaller stocks. On the other hand, our results and the previous literature show the relevant role of these stocks in the relationship between past $1-R^2$ or idiosyncratic volatility and performance[8]. The above issues highlight the possibility of finding different evidence under different frameworks.

3.2 Other additional analysis not shown in the main paper

3.2.1 Performance of quintile portfolios based on past (previous two months) R^2

The results shown in the paper correspond to the application of Algorithm I, in which R^2 in step 1 is estimated for the previous two years' data. Since we are using daily data, it is possible to consider a shorter time period to estimate the R^2 of each investment. This additional analysis has a dual interest. First, it will account for the possibility that factor loadings may vary at higher frequencies. This question is especially relevant because it is known that when time-varying parameters are considered, the fit of the model is better and this affects the R^2, an essential element in the formation of the quintile portfolios. The second point of interest is that using a different window will serve to test the robustness of the main results.

[8] Huang et al. (2010) show that forming value weighted portfolios enhances the negative relation found by Ang et al. (2006). In this sense, if we compare the first rows of panels A and B of Table W12, we find that, on average, mutual fund investment is closer to an equally weighted market portfolio than to a value weighted case.

Table W20 shows the results obtained by using a two-month rolling window instead of the two years corresponding to results in Table 4 in the paper. A comparison of the two tables shows that the performance is slightly better in the case of *Mutual funds*, *French Industries portfolios* and *Synthetic funds*, but that it is lower in the case of *Stocks*. However, although there are some differences in the value of the abnormal performance of the *Low-High* portfolio quintile, the results are similar, thus maintaining the evidence found in Table 4. In the rest of the paper we will therefore continue to show the results obtained in the main analysis with the two-year window.

3.2.2 Analysis of additional factors in performance measurement models

As we show in Appendix 1 of this 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. If there is a relationship between these factors and future performance, there will be an implicit relationship between the idiosyncratic risk of this portfolio and its performance. We therefore explore whether incorporating additional factors in the performance models produces similar or different results. We consider two possible factors: aggregate volatility, and a mimicking portfolio for the relationship between the percentage of idiosyncratic risk and performance. Below we report the results for the case of aggregate volatility; the results for the mimicking portfolio are provided in the main paper.

Volatility has been shown to be significantly priced in the cross section of stock returns (Ang et al. 2006). We proxy aggregate volatility by the VIX index from the Chicago Board Options Exchange (CBOE). As the VIX index is serially correlated, following Ang et al. (2006) we use daily first differences in VIX as an additional factor. Thus, firstly, we again implement Algorithm I in all investment sets; the extended performance models 4F, 5F and 7F incorporating the VIX factor are therefore applied in step 1. Steps 2 to 4 are then carried out. Next, in step 5 we compute the returns of each quintile portfolio and then estimate its abnormal performance. In order to analyze the explanatory power of the additional factor, in step 5 we estimate the performance in two different ways. On the one hand, we apply the performance models without the additional factor. The objective is to analyze whether including this additional factor has a relevant effect on the development of steps 1 to 4 of Algorithm I; that is, whether the

VIX factor is able to modify the R^2 of the investments in such a way that the quintile portfolios are different from those obtained initially, the results of which were shown in Table 4 of the main paper. However, because the results are practically the same as in Table 4, to save space they are not shown. On the other hand, in step 5 we also apply the performance models with the additional factor. The results for the whole sample period are displayed in Table W18. Panel A shows how the VIX factor takes a negative sign (in line with Ang et al. 2006) in all investments and models, being significant in the vast majority of cases. Panel B shows the annualized performance of the *Low-High* quintile portfolio obtained by applying Algorithm I. The results are practically the same as the corresponding ones in Panel A of Table 4; the only differences are for the *French industries portfolios*, although in any case the non-significance of their alphas holds. Therefore, the inclusion of the VIX factor does not modify the previous results either in the first four steps of the algorithm or in the fifth step.

3.2.3 The role of fund costs

Managers provide added value for the fund's investors if adjusted gross return exceeds management costs. Therefore, if the objective is to evaluate this added value, performance measures usually use net returns. As our objective is to evaluate whether investment strategies based on past R^2 can be exploited by investors, we follow Amihud and Goyenko (2013) in using net returns. However, we will also explore whether costs have any effect in this analysis. Firstly, it should be noted that the correlation between the average expense ratio and the mutual funds' R^2 for the entire sample period is -0.24, that is, as Panel A of Table W19 also shows, funds with lower (higher) R^2 bear more (fewer) expenses. Panel B shows the results of applying Algorithm I with the gross returns of the funds with model 4F. Panel C shows the differences regarding the results with net returns (Table 1 of the main paper). With gross returns obviously performance improves. This effect is greater as R^2 decreases, hence the difference in annualized performance between *Low-High* is 1.85%, higher than the 1.40% in Table 1 with net returns. Therefore, the evidence of an inverse relationship between past R^2 and abnormal performance holds, and is even more intense. On the other hand, Algorithm I is also applied using gross returns and the 4F model with the *ImS* additional factor. The results, shown in Panel D, yield the same evidence as with net returns (in Table 3 of the main paper): when the *ImS* factor is incorporated, the inverse relationship between past

R^2 and abnormal performance vanishes. Similar to Panel C, Panel E shows that performance improves with gross returns. In sum, the previous evidence using net returns holds and is not driven by expenses.

3.2.4 Comparing the performance linked to past R^2 of mutual funds and artificial portfolios

The previous sections have shown how the inverse relation between past R^2 and future performance is found in both mutual funds and artificial investments. In Table 3, when the *ImS* factor is considered in the 4F model, this relation vanishes. Now Table W20 shows the complete results for different performance models, both for mutual funds and artificial portfolios. Panel A shows how the *ImS* factor is significant and positive for all investments and models. Panel B shows the annualized performance of the *Low-High* quintile portfolios. Only in the case of the *EW stock portfolio* is it positive and significant. In the case of *Synthetic funds*, performance is not significant. In general, these results are very different from those shown for Table 4 with the models in which the additional factor was not included. Therefore, the previous evidence does not hold and the abnormal performance is generally lower.

In the performance models, we compare the active management of mutual funds with the passive character of the risk factors. By including *ImS* as an additional factor we also adjust mutual fund returns to the return of a strategy based on R^2 for a set of artificial investments, the *Stocks* set in this case. Alternatively, and as a robustness analysis, we can also compare with other artificial portfolios that follow the same strategy. Then, Table W18 shows the differences between the performance of investment strategies based on past R^2 for mutual funds and that achieved respectively for the case of artificial portfolios, from data of Table 4. For comparative purposes we only considered portfolios as artificial investments and not individual stocks. The results for columns (1) to (5) indicate that when comparing the performance of the mutual funds with that of artificial portfolios, either there are no differences between them or it is worse for mutual funds. Let us recall that from the investors' perspective, mutual funds have been assessed using net returns, so it is usual to find that mutual funds underperform.

One could argue that artificial portfolios used above may have different styles from the mutual funds analyzed. Therefore, to improve the comparability we now compare the performance of investment strategies based on past R^2 for mutual funds and their synthetic counterparts.[9] Column (6) in Table W18 shows the difference between the performance of mutual funds and that of synthetic funds. In all the cases, for all models and panels according to time samples, the differences are negative and significant in general, i.e. the performance of investment strategies based on past R^2 is higher in the case of synthetic funds than for the mutual funds. For instance, in Panel A for the 4F model, this difference is -2.18% annualized. Although mutual fund returns are net of costs, this value is even higher (in absolute terms) than the average of the expense ratio, 1.31% per year (see Table W1). Therefore these results are consistent with those presented in Tables 3 and W20 when mutual returns are adjusted by including *ImS* as an additional factor. Both procedures therefore lead to the same conclusion: that the abnormal performance for mutual funds (from the perspective of the funds' investors) was not different or was even worse than that obtained by the same investment strategies in artificial portfolios[10].

3.2.5 Comparing mutual funds and synthetic funds grouped by style

Table W19 shows the differences between the performance of *Low-High* quintiles of mutual funds and their synthetic counterparts grouped by styles. The first columns on the left show the results for the whole sample period. In general, the differences are negative and significant except for some cases of the 4F model and *growth* funds. Values and significance vary across the styles and subperiods considered. For *growth* funds the differences are higher, and even positive in some cases. In contrast, *blend* categories (and *small value*) show the lower, more negative, differences. This pattern is particularly remarkable for the first subperiod, 1990-97.

In short, except for certain cases such as the *growth* funds in the first subperiod and 4F model, we found negative differences. Consequently, this means that in general the

[9] Previous literature (Bollen and Busse 2001 and 2005, Benos and Jochec 2011 and Matallín et al. 2016 among others) has also proposed using synthetic counterparts to assess mutual fund behavior. It is a nonparametric procedure that seeks to avoid artificial or passive effects which may be biasing the estimation of performance models.

[10] Although it is appropriate to clarify that no trading costs for artificial investments or sales charges and load fees for mutual funds have been considered.

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. Therefore, the results shown in column (6) of Table W18 for the whole mutual funds sample hold for the most of the category funds.

3.2.6 The cross-relationship between R^2 and the *ImS* factor

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. Table W20 shows the results obtained by applying the 4F model extended to include *ImS* as an additional factor. To save space we do not show the complete 25-cell grids for each set of portfolios; rather, we display the difference between the *Low-High* past R^2 quintile as in the previous tables.

Panel A shows the results when applying the algorithm; firstly, the portfolios are sorted in quintiles by past b_{ImS} and then, within each quintile they are ordered by past R^2. The differences between the estimates of b_{ImS} for the portfolios with the lowest and the highest R^2 are shown in subpanel A1. For example, in the first cell on the right of the subpanel, i.e. for the case of portfolios with higher b_{ImS}, 0.146 is the difference between the average value of b_{ImS} for funds with lower and higher R^2. As can be seen, the *Low-High* difference generally takes values above zero, which indicates a negative relationship between R^2 and b_{ImS}; that is, as expected, the portfolios with lower (higher) R^2 show higher (lower) b_{ImS}, or in other words, portfolios with a higher (lower) percentage of idiosyncratic risk show higher (lower) loadings on the *ImS* factor. In the case of mutual funds and synthetic funds, the difference in b_{ImS} for *Low-High* past R^2 is greater for those funds with higher levels of past b_{ImS} (last column on the right of the subpanel).

Next, subpanel A2 shows the differences in average return between the portfolios *Low-High* past R^2 within each quintile based on past b_{ImS}. In general, the differences are positive, which implies that portfolios with lower R^2 obtain higher returns than portfolios with higher R^2. Although in the next subpanel we will carry out a more suitable comparison by contrasting performance instead of return, this result obviously implies that not all the positive relationship between the percentage of idiosyncratic risk and the return of the portfolio is captured by the factor, due precisely to the idiosyncratic nature of this risk.

On the other hand, a comparison of the results obtained by the different sets of portfolios shows that the differences in return *Low-High* R^2 are in all cases higher for the artificial portfolios than for the mutual funds. For instance, for the high b_{ImS} column, the difference (annualized) is 7.09% for the case of *Synthetic funds* but negative (0.57%) for mutual funds. That is, the contribution of the percentage of idiosyncratic risk in the return of the *Synthetic funds* (artificial portfolios) is higher than the case of mutual funds. As the mutual funds' idiosyncratic risk is due to both active management and a passive effect, this implies, as already pointed out in this study, that active management does not seem to add value. In addition, as stocks are equally weighted the effect of the positive relationship between the percentage of idiosyncratic risk and return is greater than for the value weighted case, so in the same column, the difference in return is 4.14% for the case of the *EW stock portfolios*.

Subpanel A3 in Table W20 shows the difference in performance for the *Low-High* past R^2 portfolios. The first row shows the results for mutual funds. For the column of higher b_{ImS} values, we find that the performance of funds with lower R^2 is a significant 4.23% (annualized) worse than mutual funds with higher R^2. This result is in line with that shown in Tables 3 and W20, so as the *ImS* factor is considered, the previous negative relationship between past R^2 and performance shown in Tables 1 and 4 vanishes. Only for funds with lower values of b_{ImS} does the difference take a positive but not significant value of 0.49%. In sum, on analyzing portfolio abnormal performance, for mutual funds we find that as the level of the loading on the *ImS* factor increases, the previous positive relationship between the percentage of idiosyncratic risk and performance vanishes and can even become negative.

Unlike the case of mutual funds, for the artificial portfolios the differences are generally positive, taking for instance a value of 2.86% for the *EW stock portfolios* for the column of high b_{ImS}. The positive sign indicates that the performance of artificial portfolios with lower (higher) R^2 is higher (lower), which means that part of the positive relationship between the percentage of idiosyncratic risk and performance is not yet captured by the factor.

Panel B shows the results when for the variant of Algorithm I, the portfolios are grouped first by past R^2 and then each quintile is ordered by past b_{ImS}. Results are not very different from those shown in Panel A. Similarly to subpanel A1, subpanel B1 shows how the difference in the value of the estimates for b_{ImS} for *Low-High* past R^2 is again positive, taking higher values in practically all the cells of the grid. That is, further evidence is found to confirm that the portfolios with higher (lower) levels of the percentage of idiosyncratic risk show a higher (lower) loading on the *ImS* factor. In subpanel B2, the difference in return between the *Low-High* past R^2 portfolios is positive in all cases and always greater for the artificial portfolios than for mutual funds, so the conclusions drawn for the A2 subpanel can be extrapolated.

Subpanel B3 shows the difference in performance for the *Low-High* past R^2 portfolios, taking a negative value in all the quintiles for the case of mutual funds and *VW stock portfolios*. In the case of *Synthetic funds* it is also negative except for the funds with the highest value of b_{ImS}, in which only the *EW stock portfolios* are positive in all cases. In summary, the performance from following a strategy based on *Low-High* past R^2 does not provide a positive abnormal performance for either mutual funds or artificial portfolios, except in the case of some artificial portfolios with higher levels of b_{ImS} and in the case of portfolios with equally weighted stocks. In these latter cases there is still a positive relationship between the percentage of idiosyncratic risk and performance that is not captured by the *ImS* factor. These results coincide with those shown in Panel B of Table W20 in which the results of the *Low-High* past R^2 strategies yield a negative performance, except for the case of the *EW stock portfolios*.

4. Theory annex

4.1 Appendix 1

In this appendix we demonstrate how an omitted factor in the performance model affects coefficients and idiosyncratic risk estimates. First, we propose a comprehensive model with multiple factors, omitted and non-omitted. Thus, the linear model A1 is applied to performance measurement; $r_{p,t}$ 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.

$$r_{p,t} = \alpha_p + \sum_{j=1}^{J} b_j r_{j,t} + \varepsilon_{p,t} \tag{A1}$$

But if a set of *Q* risk factors is omitted, then the real performance model will be A2

$$r_{p,t} = \alpha'_p + \sum_{j=1}^{J} b'_j r_{j,t} + \sum_{q=1}^{Q} b'_q r_{q,t} + \varepsilon'_{p,t} \tag{A2}$$

Let us suppose that omitted factors can be expressed as a linear function of the non-omitted factors.

$$r_{q,t} = a_q + \sum_{j=1}^{J} c_q r_{j,t} + u_{q,t} \tag{A3}$$

Then, considering A3 and comparing terms of expressions A1 and A2 we can show the estimates when model A1 is applied:

$$\alpha_p = \alpha'_p + \sum_{q=1}^{Q} b'_q a_q \tag{A4}$$

$$b_j = b'_j + \sum_{q=1}^{Q} b'_q c_q \tag{A5}$$

$$\varepsilon_{p,t} = \varepsilon'_{p,t} + \sum_{q=1}^{Q} b'_q u_{q,t} \tag{A6}$$

As expressions A4-A6 show, the greater b'_q, the slope of the relation between the portfolio return and the omitted factor *q* in the true model A2, the greater the effect of the factor omission. In A4, the performance estimated using model A1, α_p, would be equal to the sum of the true alpha α'_p and the sum of the products between b'_q and a_q, the performance of the omitted factor with respect to the *J* non-omitted factors in A3. Regarding the effect on the idiosyncratic risk, in A7 we compute the variance from expression A6.

$$\sigma^2(\varepsilon_{p,t}) = \sigma^2(\varepsilon'_{p,t}) + \sum_{q=1}^{Q} b'^2_q \sigma^2(u_{q,t}) + \sum_{q=1}^{Q} 2b'_q\, \sigma(\varepsilon'_{p,t}, u_{q,t}) + \sum_{q=1}^{Q} \sum_{\substack{x=1 \\ x \neq q}}^{Q} b'_q b'_x \sigma(u_{q,t}, u_{x,t}) \qquad (A7)$$

Thus, the estimated idiosyncratic risk in model A1 is that from expression A2 plus the sum of the products of b'^2_q and the idiosyncratic risk of the omitted factors with respect to the non-omitted factors, plus the sum of the covariance between all error terms. In equation A7 we propose a broad model that can be simplified to specific cases. So, under the hypothesis that the covariance is zero, we have equation A8:

$$\sigma^2(\varepsilon_{p,t}) = \sigma^2(\varepsilon'_{p,t}) + \sum_{q=1}^{Q} b'^2_q \sigma^2(u_{q,t}) \qquad (A8)$$

Thus, the last term on the right of equation A8 reveals a positive relation between the portfolio's estimated idiosyncratic risk, $\sigma^2(\varepsilon_{p,t})$, the portfolio's exposure to the omitted factor, b'^2_q and the residual variance of the omitted factor with respect to the non-omitted factors. The positive relationship will be stronger, the greater the portfolio's exposure and the lower the correlation between the omitted factor and the non-omitted factors.[11] Moreover, the sign of the exposure is crucial because it also multiplies performance in expression A4. Then, suppose that there is an omitted factor which outperforms when model A3 is applied, i.e. its alpha is positive, $a_q > 0$, and that the portfolio's exposure to this factor is also positive, $b'_q > 0$. Therefore, the portfolio's alpha, α_q, will increase according to A4 and the idiosyncratic risk, $\sigma^2(\varepsilon_{p,t})$, will also increase according to A8. A positive relation between the above two variables can thus be found. The sign of this relation is an empirical issue depending on the omitted factor's performance with regard to the non-omitted factors. So, when the omitted factor outperforms (underperforms), its alpha will be positive (negative) but the portfolio's idiosyncratic risk will increase, and then evidence of a positive (negative) relationship between portfolio performance and idiosyncratic risk would be found. If the portfolio's exposure is negative, $b'_q < 0$, the opposite reasoning would apply.

[11] In fact, the residual variance of the omitted factor can be replaced by its total variance if we assume that the omitted factor is orthogonal to the set of non-omitted factors, as Chen and Petkova (2012) propose analyzing the relation between asset's idiosyncratic risk and expected returns.

In view of the above, portfolios investing in asset classes mispricing relative to non-omitted factors in model A1 would display higher idiosyncratic risk and their performance would probably be different from zero, since the sign of this performance is an empirical issue. Thus, the existence of some level of short-term persistence or *momentum* in the performance of omitted factors would drive a performance different from zero in investment strategies based on past portfolio's percentage of idiosyncratic risk.

4.2 Appendix 2

In this appendix we show how idiosyncratic risk reflects active management. As the well known expression A9 shows, the idiosyncratic risk of the portfolio in A1 is a function of the error terms of each stock i when the linear asset pricing model is applied with J factors, where w_i is the weight of each of the N stocks in the portfolio. A similar expression would be obtained from A2 for the model of $J+Q$ factors. It is certain that this risk can be reduced by diversification, but it is only guaranteed to be zero when the portfolio is an exact linear combination of the factors. In the other case, which occurs frequently, it would take value greater than zero even for a passive portfolio.

$$\sigma^2\left(\varepsilon_{p,t}\right) = \sigma^2\left(\sum_{i=1}^{N} w_i \varepsilon_{i,t}\right) \tag{A9}$$

How can we capture active management with idiosyncratic risk? One way to do this is by the opposite of a passive *buy-and-hold* strategy. Thus, in order to add value to the investor, by *stock selection* or *market timing*, active management involves buying and selling assets. This implies that the weights of the stocks vary at some point in time. Therefore, the elements of expression A1 are redefined as a function of the weight of each asset at the beginning of period, $w_{i,t}$, as shown by A10, A11 and A12.

$$\alpha_{p,t} = \sum_{i=1}^{N} w_{i,t} \alpha_i \tag{A10}$$

$$b_{j,t} = \sum_{i=1}^{N} w_{i,t} b_{ij} \tag{A11}$$

$$\varepsilon^*_{p.t} = \sum_{i=1}^{N} w_{i,t} \varepsilon_{i,t} \tag{A12}$$

Consequently, a more complex expression of the variance is obtained in A13, which depends on the variances and covariances of a greater number of elements that can interact with each other.

$$\sigma^2\left(r_{p,t}\right) = \sigma^2\left(\alpha_{p,t} + \sum_{j=1}^{J} b_{j,t} r_{j,t} + \varepsilon^*_{p,t}\right) \quad \text{(A13)}$$

In this case, it is not possible to define the idiosyncratic risk directly as in expression A9, but as a difference between the total risk and the systematic risk. In turn, within the idiosyncratic risk we can distinguish two components, *active* idiosyncratic risk, derived from active management and *passive* idiosyncratic risk, due to the idiosyncratic risk from stocks held in the portfolio. One way to differentiate between the two components is to compare the idiosyncratic risk of the active portfolio with that obtained by an artificial portfolio that replicates its average style.

This artificial portfolio can be defined by the vector of average weights of each asset in the portfolio. In this way, we can express $w_{i,t}$ as the sum of the average weight w_i and the difference $d_{i,t}$ and therefore from A13 we would achieve expression A14. Omitting for simplicity all the covariances between the different variables, expression A14 could be presented as A15 and A16, where the first term on the right would be associated with systematic risk, the second would be the part of idiosyncratic risk linked to active management and the third term the part of this risk that corresponds to a passive component. In the case of no active management, the variable $d_{i,t}$ would be zero and therefore the only component of the idiosyncratic risk would be that *passive* in this third term, coinciding with what is specified in A9.

$$\sigma^2\left(r_{p,t}\right) = \sigma^2\left(\sum_{i=1}^{N}\left(w_i + d_{i,t}\right)\alpha_i + \sum_{j=1}^{J}\sum_{i=1}^{N}\left(w_i + d_{i,t}\right)b_{ij} r_{j,t} + \sum_{i=1}^{N}\left(w_i + d_{i,t}\right)\varepsilon_{i,t}\right) \quad \text{(A14)}$$

$$\sigma^2\left(r_{p,t}\right) = \sigma^2\left(\sum_{j=1}^{J}\sum_{i=1}^{N} w_i b_{ij} r_{j,t}\right) + \sigma^2\left(\sum_{i=1}^{N} d_{i,t}\alpha_i + \sum_{j=1}^{J}\sum_{i=1}^{N} d_{i,t} b_{ij} r_{j,t} + \sum_{i=1}^{N} d_{i,t}\varepsilon_{i,t}\right) + \sigma^2\left(\sum_{i=1}^{N} w_i \varepsilon_{i,t}\right) \quad \text{(A15)}$$

$$\sigma^2\left(r_{p,t}\right) = \sigma^2\left(\sum_{j=1}^{J} b_j r_{j,t}\right) + \sigma^2\left(\sum_{i=1}^{N} d_{i,t}\alpha_i + \sum_{j=1}^{J}\sum_{i=1}^{N} d_{i,t} b_{ij} r_{j,t} + \sum_{i=1}^{N} d_{i,t}\varepsilon_{i,t}\right) + \sigma^2\left(\varepsilon_{p,t}\right) \quad \text{(A16)}$$

If, as explained in Appendix 1, there are Q omitted factors with explanatory power on stock returns and therefore on the portfolios, the two components of idiosyncratic risk will be affected, both *active* and *passive*, the latter as indicated in expression A8.

4.3 Appendix 3

Amihud and Goyenko (2013) propose using the level of idiosyncratic risk as a measure of mutual fund active management. In appendix 2 we propose a model which shows how idiosyncratic risk captures both active management and a passive component linked to the idiosyncratic risk of the stocks in the portfolio. In Appendix 1 we show how omitted factors, included in the passive component of idiosyncratic risk, can explain the relationship between past percentage of idiosyncratic risk and performance. Next in this appendix we outline the relationship between Cremers and Petajisto's (2009) active management measure and the model proposed in Appendix 2, and with Amihud and Goyenko's (2013) measure.

Expression A17 shows the active management measure proposed by Cremers and Petajisto (2009) labeled as *Active Share*,

$$ActiveShare = \frac{1}{2}\sum_{i=1}^{N}\left|w_{p,i} - w_{B,i}\right| \tag{A17}$$

where $w_{p,i}$ is the weighting of stock i in mutual fund p, and $w_{B,i}$ is the weight of the stock in the index benchmark for that mutual fund. In this measure, there will be active management if, in general, $w_{p,i}$ is different from $w_{B,i}$.

Firstly, we compare *Active Share* with the model proposed in Appendix 2. Both approaches define active management as the existence of differences in the portfolio stock weights. However, in the *Active Share* measure the differences are in relation to the benchmark, while in our model they lie in the average style of the mutual fund. We think that our model offers several advantages over *Active Share*. Firstly it is more versatile because it measures active management not only against a benchmark but also with respect to the average style of the mutual fund. The style represents the passive management and it could be defined as the average investment in several style stocks or benchmarks in line with previous literature such as Sharpe (1992), Daniel et al. (1997) and Bollen and Busse (2001), among others. The second advantage of our model is that, also in line with this previous literature, it considers the dynamism at the time of the changes in the stocks' weights as the main evidence of active management of the mutual fund. Thus, for example, a non-index mutual fund which follows a buy-and-hold strategy will show evidence of active management using the *Active Share* measure but not using our model. The third advantage of our model is that, as shown by the expression A16, it integrates the effect of active management into the risk of the fund, differentiating between passive systematic risk and idiosyncratic risk, and within the latter, also in turn considering both the active and passive components.

Secondly, we show the relationship between the *Active Share* measure and others such as Amihud and Goyenko's (2013), which link active management with the percentage of idiosyncratic risk. From A17, the expression A18 shows how the relevant element of the *Active Share* measure is the difference between the weights of the stocks in the portfolio *p* and in the benchmark index *B*.

$$f_i = w_{p,i} - w_{B,i} \tag{A18}$$

In A19 the return of mutual fund *p* can be expressed as the weighting sum of the stocks' returns, thus yielding expression A20.

$$r_{p,t} = \sum_{i=1}^{N} w_{p,i} r_{i,t} = \sum_{i=1}^{N} (w_{B,i} + f_i) r_{i,t} \tag{A19}$$

$$r_{p,t} = r_{B,t} + \sum_{i=1}^{N} f_i r_{i,t} \tag{A20}$$

For simplicity we only consider one factor in A1—the excess market return (CAPM model); therefore A20 can be expressed as A21 and A22.

$$r_{p,t} = \alpha_B + b_B r_{M,t} + \varepsilon_{B,t} + \sum_{i=1}^{N} f_i (\alpha_i + b_i r_{M,t} + \varepsilon_{i,t}) \tag{A21}$$

$$r_{p,t} = \alpha_B + \alpha_{p,f} + (b_B + b_{p,f}) r_{M,t} + \varepsilon_{B,t} + \varepsilon_{p,f,t} \tag{A22}$$

If we apply Jensen (1968) to the mutual fund return, we will find that under the framework of the *Active Share* measure, and with respect to A22, the abnormal performance will be the sum of both the alpha of the benchmark, α_B and that of the active management strictly speaking, $\alpha_{p,f}$. Even if there were no active management, i.e. if f_i were equal to zero, a nonzero alpha would be found, given that it would be equal to α_B. This issue could drive the critical results of Frazzini et al. (2016) on Cremers and Petajisto's (2009) measure, since different mutual funds could show different alphas not because of their active management, but because of the different performance of their benchmarks when they are compared in aggregate and not when they are compared within the same style or group of mutual funds.

If we compute the variance in the expression A22, the risk of the mutual fund could be expressed as A23, where the null covariances by definition have not been included.

$$\sigma^2(r_{p,t}) = (b_B + b_{p,f})^2 \sigma^2(r_{M,t}) + \sigma^2(\varepsilon_{B,t}) + \sigma^2(\varepsilon_{p,f,t}) + \sigma(\varepsilon_{B,t}, \varepsilon_{p,f,t}) \qquad \text{(A23)}$$

The last three terms to the right of expression A23 make up the idiosyncratic risk of the mutual fund, which is the basis of Amihud and Goyenko's (2013) measure. As noted, this risk not only includes the idiosyncratic risk that we could link to active management, i.e. $\sigma^2(\varepsilon_{p,f,t})$ and $\sigma(\varepsilon_{B,t}, \varepsilon_{p,f,t})$, but also the passive idiosyncratic risk of the benchmark with the factor $\sigma^2(\varepsilon_{B,t})$. Thus, part of the idiosyncratic risk differences and their relation to performance would be implicitly driven by the classes of stocks in which the mutual funds invest and that can be represented by some style benchmarks. For this reason, in our study the evidence when we apply Amihud and Goyenko's (2013) methodology separately within each group of mutual funds (section 3.1.4) is scarcer than that found when it is applied for the mutual funds as a whole (section 4.2.1 of the main paper).

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6. Tables and figures

Table W1: Summary statistics for the mutual fund and factors in the sample

The sample runs from January 1990 to June 2015. Panel A shows the number of mutual funds, average expense ratio, average annualized net return and average annualized standard deviation (s.d.). Mutual funds are grouped according to the Morningstar Style box. Panel B shows the annualized mean of return and risk (measured by s.d.) for factors used in model (1).

PANEL A: Mutual funds

	Small Growth	Small Blend	Small Value	Mid Growth	Mid Blend	Mid Value	Large Growth	Large Blend	Large Value	Index	All
Sample 1990-06/2015											
# funds	435	319	208	435	220	197	870	878	651	254	4,467
Average of expense ratio	1.53%	1.40%	1.43%	1.47%	1.38%	1.35%	1.34%	1.24%	1.27%	0.62%	1.31%
Average of annualized net return	8.69%	9.46%	8.20%	7.92%	8.24%	8.92%	6.36%	6.85%	7.70%	7.09%	7.59%
Average of annualized s.d.	24.03%	21.95%	21.04%	23.38%	20.85%	20.37%	21.75%	18.76%	19.45%	21.25%	21.06%
Subsample 1990-1997											
# funds	128	72	40	124	67	43	267	280	195	62	1,278
Average of expense ratio	1.54%	1.53%	1.40%	1.63%	1.41%	1.65%	1.39%	1.30%	1.32%	0.52%	1.38%
Average of annualized net return	17.07%	17.27%	19.09%	17.42%	16.88%	15.47%	18.04%	17.01%	17.83%	18.26%	17.48%
Average of annualized s.d.	15.27%	12.11%	10.70%	15.04%	12.18%	11.06%	14.43%	12.15%	10.74%	13.02%	12.96%
Subsample 1998-2007											
# funds	346	226	144	350	149	131	702	659	511	207	3,425
Average of expense ratio	1.56%	1.49%	1.47%	1.50%	1.48%	1.32%	1.37%	1.27%	1.33%	0.67%	1.34%
Average of annualized net return	9.40%	9.17%	7.87%	8.69%	9.40%	8.41%	4.89%	6.02%	7.50%	5.25%	7.10%
Average of annualized s.d.	22.61%	18.37%	16.80%	22.78%	18.29%	16.60%	20.77%	17.22%	16.68%	19.61%	19.21%
Subsample 2008-06/2015											
# funds	290	255	140	292	148	145	588	527	442	167	2,994
Average of expense ratio	1.47%	1.47%	1.39%	1.38%	1.33%	1.25%	1.24%	1.15%	1.18%	0.54%	1.25%
Average of annualized net return	7.39%	9.02%	8.99%	5.54%	7.43%	8.77%	5.75%	5.86%	5.17%	7.68%	6.59%
Average of annualized s.d.	27.24%	26.47%	26.57%	26.06%	24.71%	24.98%	23.84%	22.81%	24.28%	24.77%	24.77%

PANEL B: Factors

	Mkt-Rf	SMB	HML	RMW	CMA	WML	MMB	SMM	BHML	SHML	MidHML	Rf
Sample 1990-06/2015												
Annualized mean return	7.91%	1.96%	2.61%	4.50%	2.95%	7.31%	1.54%	-0.27%	0.09%	7.59%	2.06%	2.96%
Annualized s.d.	17.92%	9.16%	9.44%	6.87%	6.66%	13.63%	6.02%	6.45%	14.33%	10.46%	13.64%	0.14%
Subsample 1990-1997												
Annualized mean return	10.92%	-1.12%	3.31%	6.29%	1.82%	10.61%	-0.80%	-1.18%	0.25%	11.04%	2.64%	4.82%
Annualized s.d.	11.66%	7.16%	6.38%	3.88%	5.11%	6.43%	4.97%	4.47%	11.61%	7.91%	9.69%	0.09%
Subsample 1998-2007												
Annualized mean return	4.27%	3.31%	4.43%	3.97%	4.98%	11.72%	1.88%	0.80%	0.77%	9.11%	3.54%	3.49%
Annualized s.d.	18.21%	9.95%	10.54%	9.16%	8.68%	14.15%	7.04%	7.04%	15.30%	12.02%	16.95%	0.11%
Subsample 2008-06/2015												
Annualized mean return	9.53%	3.47%	-0.58%	3.27%	1.46%	-2.11%	3.60%	-0.73%	-1.00%	1.86%	-0.54%	0.26%
Annualized s.d.	22.51%	9.94%	10.58%	5.73%	4.79%	17.93%	5.58%	7.38%	15.56%	10.64%	12.26%	0.04%

Table W2: Summary statistics for artificial investments: French's VW, EW and Industries portfolios

The data runs from January 1990 to June 2015. Panels show average annualized return and average annualized standard deviation (s.d.) of different sets of artificial investments. Firstly, panels A and B show the statistics of 300 artificial portfolios from French's data library. 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*. For exhibition purposes in this table, portfolios are grouped in deciles according their size. Stocks in the portfolios were value-weighted (VW) in Panel A and equally-weighted (EW) in Panel B. In Panel C, the third set of artificial portfolios is made up of 98 equally and value weighted portfolios, also from French's data library, formed by sorting stocks according their industrial sector

PANEL A: *French's VW portfolios* (value-weighted stocks)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	All
# portfolios	30	30	30	30	30	30	30	30	30	30	300
Sample 1990-06/2015											
Average of annualized return	13.18%	13.38%	14.18%	12.89%	13.91%	13.62%	13.31%	12.94%	13.07%	10.49%	13.10%
Average of annualized s.d.	17.36%	22.57%	22.45%	22.08%	22.21%	20.97%	20.80%	21.45%	20.84%	21.17%	21.19%
Subsample 1990-1997											
Average of annualized return	15.32%	14.49%	15.39%	14.92%	15.82%	16.46%	15.30%	14.48%	16.35%	16.64%	15.52%
Average of annualized s.d.	10.95%	12.60%	12.78%	13.12%	13.45%	13.74%	13.54%	13.62%	14.05%	15.46%	13.33%
Subsample 1998-2007											
Average of annualized return	13.89%	13.04%	12.86%	10.77%	12.49%	10.42%	12.79%	12.12%	12.14%	6.86%	11.74%
Average of annualized s.d.	15.02%	20.53%	21.73%	21.77%	22.45%	20.92%	20.43%	21.32%	20.65%	21.58%	20.64%
Subsample 2008-06/2015											
Average of annualized return	9.92%	12.63%	14.66%	13.52%	13.74%	14.82%	11.84%	12.39%	10.78%	8.70%	12.30%
Average of annualized s.d.	24.33%	31.56%	30.08%	28.96%	28.42%	26.49%	26.65%	27.37%	26.32%	25.30%	27.55%

PANEL B: *French's EW portfolios* (equally-weighted stocks)

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	All
# portfolios	30	30	30	30	30	30	30	30	30	30	300
Sample 1990-06/2015											
Average of annualized return	32.51%	16.12%	16.00%	14.28%	15.03%	14.83%	14.13%	13.65%	13.83%	11.81%	16.22%
Average of annualized s.d.	14.72%	23.03%	22.80%	22.72%	23.07%	21.64%	21.70%	22.32%	21.76%	21.70%	21.55%
Subsample 1990-1997											
Average of annualized return	50.49%	20.25%	18.51%	16.70%	17.11%	17.89%	16.16%	15.39%	16.91%	16.58%	20.60%
Average of annualized s.d.	11.20%	12.68%	12.80%	13.12%	13.64%	13.79%	13.59%	13.74%	14.10%	14.80%	13.35%
Subsample 1998-2007											
Average of annualized return	27.90%	14.07%	13.77%	11.86%	12.80%	11.52%	13.63%	12.05%	12.69%	8.19%	13.85%
Average of annualized s.d.	12.89%	19.89%	21.30%	21.98%	22.39%	21.15%	20.83%	21.54%	21.05%	21.64%	20.47%
Subsample 2008-06/2015											
Average of annualized return	19.37%	14.44%	16.27%	14.92%	15.78%	15.96%	12.61%	13.91%	12.03%	11.48%	14.68%
Average of annualized s.d.	19.38%	33.17%	31.38%	30.39%	30.58%	28.03%	28.57%	29.31%	28.28%	27.14%	28.62%

Table W2: Summary statistics for artificial investments: French's VW, EW and Industries portfolios (Cont.)

PANEL C: *French's Industries portfolios*	
# portfolios	98
Sample 1990-06/2015	
Average of annualized return	17.59%
Average of annualized s.d.	23.02%
Subsample 1990-1997	
Average of annualized return	23.88%
Average of annualized s.d.	16.39%
Subsample 1998-2007	
Average of annualized return	15.51%
Average of annualized s.d.	22.22%
Subsample 2008-06/2015	
Average of annualized return	13.60%
Average of annualized s.d.	28.56%

Table W3: Summary statistics for artificial investments: Stocks

The data runs from January 1990 to June 2015. *VW (EW) stock portfolios* are value (equally) weighted portfolios formed randomly from a sample of stocks traded on the NYSE, AMEX and NASDAQ. Panel A shows some descriptive statistics about the portfolios' construction. Panel B shows the average annualized return and average annualized standard deviation (s.d.) of these portfolios and the sample of stocks.

PANEL A: Descriptive statistics of portfolio construction

	VW stock portfolios	EW stock portfolios
# portfolios	4,467	4,467
# stocks in the portfolios		
Average minimum number	64.58	85.87
Average	139.70	148.79
Average maximum number	177.91	179.70
Maximum weights in the portfolios		
Average minimum	2.92%	
Average	3.70%	
Average maximum	5.97%	

PANEL B: Average annualized return and standard deviation

	Stocks	VW stock portfolios	EW stock portfolios
# investments	10,973	4,467	4,467
Sample 1990-06/2015			
Average of annualized return	24.74%	21.16%	24.81%
Average of annualized s.d.	58.87%	17.00%	15.05%
Subsample 1990-1997			
Average of annualized return	30.21%	24.47%	28.35%
Average of annualized s.d.	57.55%	11.44%	10.36%
Subsample 1998-2007			
Average of annualized return	23.36%	20.96%	24.23%
Average of annualized s.d.	55.33%	15.59%	13.99%
Subsample 2008-06/2015			
Average of annualized return	21.94%	17.87%	21.78%
Average of annualized s.d.	53.60%	22.79%	19.86%

Table W4: Summary statistics for Fama-French research portfolios used for estimating synthetic funds

The data runs from January 1990 to June 2015. Panels show mean annualized return and annualized standard deviation (s.d.) of Fama-French research portfolios from French's data library. The portfolios are the benchmarks used to estimate synthetic mutual funds solving the problem defined by (2)-(5). Stocks in the portfolios were value-weighted in Panel A and equally-weighted in Panel B. Each panel shows 18 portfolios from combining stocks' characteristics. The first 6 portfolios (small value, small neutral, small growth, big value, big neutral and big growth) combine 2x3 *size* and *book-to-market* values. The next 6 (small robust, small neutral, small weak, big robust, big neutral and big weak) combine 2x3 *size* and *operating profitability* and finally (small conservative, small neutral, small aggressive, big conservative, big neutral and big aggressive) are 2x3 portfolios combining *size* and *investment*.

PANEL A: Fama-French research portfolios with value-weighted stocks

	Small Value	Small Neutral	Small Growth	Big Value	Big Neutral	Big Growth	Small Robust	Small Neutral	Small Weak	Big Robust	Big Neutral	Big Weak	Small Conser.	Small Neutral	Small Aggre.	Big Conser.	Big Neutral	Big Aggre.
Sample 1990-06/2015																		
Mean of annualized return	9.64%	14.35%	14.97%	11.30%	11.30%	11.23%	9.62%	14.24%	15.15%	8.71%	10.37%	12.15%	14.89%	14.38%	9.92%	11.88%	11.61%	10.93%
Annualized s.d.	22.05%	19.04%	19.24%	18.11%	17.90%	19.93%	21.74%	18.86%	19.37%	20.25%	18.68%	17.34%	20.90%	18.37%	21.19%	17.03%	16.95%	20.79%
Subsample 1990-1997																		
Mean of annualized return	10.03%	16.63%	18.18%	16.52%	16.46%	15.04%	9.64%	16.73%	17.54%	13.39%	14.37%	18.09%	16.22%	16.08%	11.90%	16.36%	15.61%	17.03%
Annualized s.d.	13.71%	9.10%	8.81%	13.66%	11.31%	11.32%	11.81%	9.72%	11.27%	11.15%	11.39%	13.32%	10.46%	8.51%	12.63%	11.29%	11.55%	14.35%
Subsample 1998-2007																		
Mean of annualized return	7.14%	13.39%	13.92%	7.54%	9.34%	9.71%	8.35%	13.02%	13.56%	5.53%	8.35%	8.25%	14.10%	13.73%	7.55%	9.85%	10.25%	6.41%
Annualized s.d.	23.33%	17.62%	16.10%	19.35%	16.82%	16.12%	22.60%	17.01%	17.27%	21.33%	19.23%	17.52%	20.31%	16.80%	21.25%	16.71%	16.74%	22.47%
Subsample 2008-06/2015																		
Mean of annualized return	12.55%	13.17%	12.92%	10.72%	8.37%	9.18%	11.30%	13.20%	14.72%	7.92%	8.77%	10.98%	14.51%	13.43%	10.95%	9.77%	9.14%	10.39%
Annualized s.d.	27.00%	27.05%	28.84%	20.43%	24.02%	29.49%	27.92%	26.91%	27.29%	25.62%	23.58%	20.60%	28.66%	26.37%	27.52%	21.89%	21.50%	24.04%

PANEL B: Fama-French research portfolios with equally-weighted stocks

	Small Value	Small Neutral	Small Growth	Big Value	Big Neutral	Big Growth	Small Robust	Small Neutral	Small Weak	Big Robust	Big Neutral	Big Weak	Small Conser.	Small Neutral	Small Aggre.	Big Conser.	Big Neutral	Big Aggre.
Sample 1990-06/2015																		
Mean of annualized return	20.12%	24.78%	33.79%	13.07%	13.85%	13.96%	30.98%	21.33%	21.37%	11.14%	13.74%	14.80%	37.44%	24.06%	18.95%	14.61%	14.42%	11.86%
Annualized s.d.	19.78%	16.15%	13.93%	20.62%	18.89%	19.41%	16.68%	15.45%	17.42%	22.04%	18.84%	18.66%	16.42%	14.95%	17.80%	18.76%	17.67%	22.55%
Subsample 1990-1997																		
Mean of annualized return	28.84%	36.57%	50.36%	15.77%	17.61%	16.81%	47.17%	29.46%	29.77%	14.43%	15.75%	18.34%	56.35%	33.53%	28.77%	17.51%	16.51%	16.42%
Annualized s.d.	11.54%	8.49%	7.73%	13.22%	10.43%	10.03%	9.64%	8.39%	9.74%	11.06%	10.65%	12.26%	9.28%	7.76%	10.42%	10.50%	10.05%	13.71%
Subsample 1998-2007																		
Mean of annualized return	16.37%	21.36%	29.73%	10.28%	11.78%	12.08%	26.63%	18.35%	18.32%	6.86%	12.82%	12.77%	32.74%	21.25%	15.14%	12.68%	13.14%	7.94%
Annualized s.d.	20.14%	13.72%	11.49%	22.20%	16.83%	16.05%	16.44%	12.36%	13.83%	23.82%	17.66%	17.46%	15.50%	12.26%	16.74%	17.72%	16.12%	24.11%
Subsample 2008-06/2015																		
Mean of annualized return	15.77%	16.70%	21.42%	13.88%	12.58%	13.40%	19.41%	16.57%	16.44%	13.32%	12.83%	13.70%	23.42%	17.63%	13.50%	14.08%	13.89%	12.19%
Annualized s.d.	25.47%	23.64%	20.47%	24.57%	26.86%	28.85%	22.03%	23.11%	26.01%	27.69%	25.92%	24.87%	22.44%	22.27%	24.27%	25.73%	24.68%	27.50%

Table W5: Summary statistics for artificial investments: estimated synthetic funds

The data runs from January 1990 to June 2015. Synthetic funds are estimated by solving the programming problem defined by (2)-(5). The Table shows statistics of the correlation coefficients between the returns of each mutual fund and its counterpart synthetic fund.

Style	Mean	10th percentile	Median	90th percentile	s.d.
Small Growth	0.9186	0.8430	0.9442	0.9796	0.0909
Small Blend	0.9216	0.8264	0.9590	0.9870	0.1156
Small Value	0.9036	0.7619	0.9565	0.9891	0.1347
Mid-Cap Growth	0.9107	0.8268	0.9367	0.9754	0.0967
Mid-Cap Blend	0.8978	0.7692	0.9399	0.9863	0.1431
Mid-Cap Value	0.9132	0.7969	0.9553	0.9854	0.1275
Large Growth	0.9294	0.8689	0.9555	0.9831	0.0943
Large Blend	0.9222	0.8357	0.9631	0.9905	0.1231
Large Value	0.9293	0.8559	0.9608	0.9875	0.1016
Index	0.9537	0.8715	0.9872	0.9974	0.0818
All	0.9225	0.8375	0.9552	0.9882	0.1093

Table W6. Correlation between the R^2 of mutual funds and artificial investments

This table reports the correlations between the R^2 of mutual funds and different artificial investments. Firstly, performance models 4F, 5F and 7F are applied to mutual funds and daily factor returns using a non-overlapping two-month rolling window. For each two-month subperiod, mutual funds are grouped in quintiles based on R^2. Portfolio *Low* (*High*) consists of equally-weighted investing in the mutual funds with the lowest (highest) R^2. This procedure is repeated for the artificial investments: *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; *Stocks* are the equities traded on the NYSE, AMEX and NASDAQ stock markets; from these stocks are formed the randomly artificial value (equally) weighted *VW* and *EW stock portfolios*, and finally, *Synthetic funds* is a set of p artificial portfolios estimated by solving the linear problem (2)-(5). Panel A shows the correlation between the time series of the average of R2 for mutual funds each two-month period and the one corresponding to different artificial investments. Panel B (C) shows the results only for mutual funds and artificial investments in the low (high) quintile according R^2, i.e., higher (lower) percentage of idiosyncratic risk. The *p*-value is from a Student's t-test of the linear correlation coefficient. The R^2 in the table is the square of the correlation coefficient.

Panel A. All mutual funds and artificial investments

Model		French VW portfolios	French EW portfolios	French Industries portfolios	Stocks	VW stock portfolios	EW stock portfolios	Synthetic funds
4F	Correlation	0.966	0.969	0.913	0.850	0.959	0.940	0.785
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.933	0.939	0.834	0.723	0.920	0.883	0.617
5F	Correlation	0.963	0.966	0.904	0.851	0.959	0.939	0.771
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.927	0.933	0.817	0.725	0.919	0.882	0.594
7F	Correlation	0.964	0.967	0.908	0.852	0.954	0.938	0.781
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.929	0.936	0.824	0.726	0.911	0.880	0.610

Panel B. Low quintile R^2 for mutual funds and artificial investments

Model		French VW portfolios	French EW portfolios	French Industries portfolios	Stocks	VW stock portfolios	EW stock portfolios	Synthetic funds
4F	Correlation	0.921	0.925	0.839	0.643	0.916	0.900	0.719
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.847	0.856	0.705	0.413	0.839	0.810	0.517
5F	Correlation	0.904	0.908	0.819	0.609	0.912	0.890	0.683
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.816	0.824	0.670	0.371	0.832	0.793	0.466
7F	Correlation	0.917	0.919	0.842	0.583	0.910	0.894	0.724
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.841	0.844	0.710	0.340	0.829	0.800	0.524

Panel C. High quintile R^2 for mutual funds and artificial investments

Model		French VW portfolios	French EW portfolios	French Industries portfolios	Stocks	VW stock portfolios	EW stock portfolios	Synthetic funds
4F	Correlation	0.919	0.920	0.890	0.808	0.949	0.876	0.729
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.845	0.847	0.793	0.652	0.900	0.767	0.531
5F	Correlation	0.931	0.927	0.895	0.815	0.953	0.883	0.778
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.866	0.859	0.801	0.664	0.908	0.779	0.605
7F	Correlation	0.944	0.943	0.909	0.835	0.965	0.908	0.863
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	R^2	0.891	0.890	0.826	0.698	0.931	0.824	0.744

Table W7. Regression of the performance of quintile portfolios based on past R^2

This table explains the performance of the mutual funds' quintile portfolios based on past R^2 using the performance of the artificial quintile portfolios based on past R^2. Models 4F, 5F and 7F are applied using a non-overlapping 2-month rolling window over daily returns of quintile portfolios formed following Algorithm I. The intercept has been annualized and expressed as a percentage. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Quintile portfolio	Low			High			Low-High		
Model	4F	5F	7F	4F	5F	7F	4F	5F	7F
Intercept	-3.93%	-2.32%	-3.28%	-1.77%	-1.66%	-1.88%	-1.95%	-1.08%	-1.74%
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.036)	(0.001)
VW stock portfolios	0.10	0.07	0.40	0.015	0.09	0.08	0.73	0.28	0.57
	(0.415)	(0.595)	(0.041)	(0.823)	(0.067)	(0.407)	(0.000)	(0.208)	(0.032)
EW stock portfolios	-0.13	-0.06	-0.19	-0.076	-0.12	-0.13	-0.61	-0.46	-0.48
	(0.119)	(0.490)	(0.043)	(0.011)	(0.000)	(0.008)	(0.004)	(0.011)	(0.013)
French VW portfolios	0.32	0.31	0.22	0.059	0.07	0.17	0.21	0.23	0.18
	(0.040)	(0.004)	(0.024)	(0.080)	(0.086)	(0.000)	(0.018)	(0.001)	(0.010)
French EW portfolios	0.04	0.02	-0.01	-0.023	-0.06	-0.07	0.02	0.04	-0.001
	(0.530)	(0.729)	(0.910)	(0.542)	(0.057)	(0.074)	(0.575)	(0.362)	(0.985)
French Industries portfolios	-0.01	-0.03	0.02	0.070	0.05	0.08	-0.03	-0.05	-0.01
	(0.753)	(0.298)	(0.571)	(0.009)	(0.003)	(0.003)	(0.284)	(0.113)	(0.746)
Synthetic funds	0.75	0.39	0.52	0.292	0.50	0.36	0.82	0.47	0.63
	(0.000)	(0.000)	(0.000)	(0.172)	(0.009)	(0.070)	(0.000)	(0.000)	(0.000)
R^2	0.46	0.27	0.34	0.12	0.21	0.26	0.53	0.37	0.38

Table W8. Performance of *Low-High* quintile portfolios based on past R^2 of mutual funds, grouped by style

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 mutual funds' past R^2. Following Algorithm I, using daily returns from the previous two years, performance models 4F, 5F and 7F are applied. Mutual funds are grouped according style. Within each style group 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 quintile portfolios up to *High*, which invests in the 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 is estimated respectively by means of 4F, 5F and 7F models. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

	All sample 1990-2015			Subsample 1990-1997			Subsample 1998-2007			Subsample 2008-2015		
Style	4F	5F	7F	4F	5F	7F	4F	5F	7F	4F	5F	7F
Small Growth	1.557	0.184	1.632	2.995	0.579	1.107	4.225	2.472	4.264	-2.952	-2.126	-2.986
	(0.100)	(0.850)	(0.070)	(0.085)	(0.755)	(0.504)	(0.004)	(0.125)	(0.001)	(0.027)	(0.086)	(0.023)
Small Blend	1.507	0.566	1.655	1.952	-1.356	-1.330	2.891	2.096	3.101	-0.575	0.045	-0.840
	(0.132)	(0.576)	(0.088)	(0.337)	(0.495)	(0.504)	(0.044)	(0.164)	(0.021)	(0.716)	(0.977)	(0.571)
Small Value	2.929	3.441	3.350	1.544	1.399	1.189	5.057	5.558	5.558	0.058	1.058	-0.455
	(0.013)	(0.002)	(0.004)	(0.446)	(0.459)	(0.533)	(0.003)	(0.000)	(0.001)	(0.978)	(0.619)	(0.829)
Mid-Cap Growth	0.656	-0.869	1.624	4.651	2.678	2.485	2.323	0.744	3.296	-2.914	-2.372	-2.136
	(0.533)	(0.435)	(0.104)	(0.021)	(0.159)	(0.190)	(0.203)	(0.700)	(0.052)	(0.008)	(0.031)	(0.030)
Mid-Cap Blend	1.908	1.439	2.451	6.528	4.419	2.940	3.256	2.947	3.040	-2.499	-1.810	-0.443
	(0.037)	(0.109)	(0.006)	(0.001)	(0.018)	(0.116)	(0.022)	(0.032)	(0.013)	(0.041)	(0.148)	(0.752)
Mid-Cap Value	0.766	0.153	0.619	2.433	0.072	1.069	1.759	1.118	1.461	-0.986	0.062	-0.833
	(0.327)	(0.840)	(0.394)	(0.161)	(0.964)	(0.475)	(0.109)	(0.309)	(0.181)	(0.398)	(0.959)	(0.446)
Large Growth	1.190	1.243	1.368	3.072	2.764	2.476	2.301	2.238	2.628	-1.046	-0.384	-1.304
	(0.039)	(0.028)	(0.011)	(0.001)	(0.000)	(0.001)	(0.013)	(0.013)	(0.003)	(0.232)	(0.638)	(0.103)
Large Blend	0.813	0.768	0.924	1.245	1.485	0.565	1.579	1.660	2.066	-0.327	-0.315	-0.779
	(0.140)	(0.159)	(0.076)	(0.273)	(0.173)	(0.601)	(0.024)	(0.024)	(0.002)	(0.703)	(0.696)	(0.332)
Large Value	1.073	0.953	0.889	0.971	0.677	0.331	1.699	2.259	1.953	-0.321	-0.411	-0.749
	(0.069)	(0.113)	(0.131)	(0.286)	(0.460)	(0.702)	(0.105)	(0.025)	(0.070)	(0.725)	(0.684)	(0.398)
Index	0.367	1.098	-0.170	0.516	2.292	1.491	0.766	1.130	-0.588	0.229	0.907	0.380
	(0.614)	(0.129)	(0.804)	(0.730)	(0.125)	(0.324)	(0.500)	(0.321)	(0.560)	(0.834)	(0.404)	(0.711)

Table W9. Performance of low-high quintile portfolios based on past R^2 of *French VW* and *EW* artificial portfolios grouped by size

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 the sets of *French VW portfolios* and *French EW portfolios*. Following Algorithm I, using daily returns from the previous two years, performance models 4F, 5F and 7F are applied. Artificial portfolios are grouped in deciles according to stock size. Within each decile group, artificial portfolios are grouped in quintiles based on past R^2. Portfolio *Low* consists of equally-weighted investing, over the next month, in the portfolios 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 portfolios 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 is estimated respectively by means of 4F, 5F and 7F models. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Panel A: French VW portfolios

	All sample 1990-2015			Subsample 1990-1997			Subsample 1998-2007			Subsample 2008-2015		
Size decile	4F	5F	7F	4F	5F	7F	4F	5F	7F	4F	5F	7F
Low	5.737	4.333	4.622	13.662	11.258	9.849	5.256	4.447	3.969	1.626	1.905	1.499
	(0.001)	(0.004)	(0.005)	(0.000)	(0.000)	(0.000)	(0.061)	(0.085)	(0.110)	(0.427)	(0.287)	(0.437)
D2	5.405	3.217	3.770	12.682	9.238	5.716	4.861	3.094	2.763	0.903	0.761	2.410
	(0.000)	(0.019)	(0.003)	(0.000)	(0.000)	(0.000)	(0.067)	(0.183)	(0.164)	(0.615)	(0.678)	(0.191)
D3	4.640	2.926	3.297	10.365	7.152	2.884	3.385	2.823	1.520	2.702	2.236	3.426
	(0.004)	(0.045)	(0.026)	(0.000)	(0.000)	(0.083)	(0.136)	(0.165)	(0.430)	(0.283)	(0.335)	(0.150)
D4	2.549	1.560	2.469	5.776	5.189	-0.008	4.795	4.022	3.670	-2.780	-1.096	0.121
	(0.096)	(0.242)	(0.070)	(0.012)	(0.026)	(0.997)	(0.040)	(0.042)	(0.052)	(0.231)	(0.624)	(0.955)
D5	2.212	-0.342	1.188	0.085	0.885	-0.753	3.171	-0.594	1.709	3.781	4.427	2.694
	(0.174)	(0.809)	(0.428)	(0.969)	(0.680)	(0.721)	(0.226)	(0.783)	(0.453)	(0.112)	(0.049)	(0.245)
D6	3.112	0.352	1.793	3.957	2.551	1.943	3.875	0.616	0.247	-0.445	-0.524	-0.619
	(0.053)	(0.809)	(0.206)	(0.134)	(0.313)	(0.410)	(0.155)	(0.786)	(0.910)	(0.848)	(0.820)	(0.784)
D7	1.150	0.087	0.753	-2.030	-3.238	-2.391	2.070	2.889	1.592	2.114	2.449	1.478
	(0.431)	(0.953)	(0.591)	(0.482)	(0.251)	(0.340)	(0.365)	(0.216)	(0.473)	(0.322)	(0.238)	(0.476)
D8	-0.863	-3.383	0.357	-3.067	-3.352	-2.734	1.516	-1.214	2.781	-2.079	-1.589	-2.750
	(0.596)	(0.031)	(0.812)	(0.221)	(0.168)	(0.205)	(0.586)	(0.629)	(0.236)	(0.380)	(0.488)	(0.225)
D9	1.132	0.569	2.245	2.663	2.342	2.895	0.413	-0.019	2.530	0.954	2.808	1.587
	(0.473)	(0.715)	(0.155)	(0.314)	(0.345)	(0.234)	(0.857)	(0.993)	(0.261)	(0.772)	(0.398)	(0.633)
High	-2.158	-0.469	0.215	-7.897	0.676	1.229	-3.106	-3.071	-0.760	-2.144	0.504	-2.608
	(0.224)	(0.781)	(0.892)	(0.010)	(0.812)	(0.624)	(0.266)	(0.228)	(0.756)	(0.471)	(0.855)	(0.359)

Panel B: French EW portfolios

	All sample 1990-2015			Subsample 1990-1997			Subsample 1998-2007			Subsample 2008-2015		
Size decile	4F	5F	7F	4F	5F	7F	4F	5F	7F	4F	5F	7F
Low	0.438	-0.662	-1.861	-2.737	-4.966	-6.327	0.563	-0.279	-3.322	3.757	4.126	3.327
	(0.795)	(0.654)	(0.264)	(0.153)	(0.008)	(0.001)	(0.850)	(0.916)	(0.228)	(0.095)	(0.037)	(0.122)
D2	4.107	2.500	1.417	9.482	6.128	3.199	3.752	2.788	-0.872	0.672	1.339	2.521
	(0.007)	(0.070)	(0.324)	(0.000)	(0.001)	(0.052)	(0.142)	(0.225)	(0.699)	(0.729)	(0.509)	(0.208)
D3	5.442	3.992	1.784	9.595	6.595	2.488	5.072	4.616	1.441	2.856	3.210	0.005
	(0.001)	(0.008)	(0.240)	(0.000)	(0.001)	(0.185)	(0.054)	(0.055)	(0.521)	(0.245)	(0.175)	(0.998)
D4	2.997	1.547	1.297	6.603	5.018	0.153	3.748	3.680	1.583	-1.057	-1.076	-0.810
	(0.082)	(0.308)	(0.394)	(0.002)	(0.020)	(0.939)	(0.168)	(0.133)	(0.482)	(0.679)	(0.678)	(0.735)
D5	2.469	1.772	1.726	1.188	1.563	-1.055	0.866	2.533	0.724	6.200	6.976	5.798
	(0.169)	(0.249)	(0.284)	(0.583)	(0.467)	(0.626)	(0.760)	(0.303)	(0.762)	(0.032)	(0.011)	(0.031)
D6	2.485	0.673	1.661	3.794	2.632	1.868	2.486	0.610	0.188	-1.259	0.771	-0.680
	(0.187)	(0.685)	(0.325)	(0.164)	(0.308)	(0.450)	(0.463)	(0.829)	(0.946)	(0.589)	(0.746)	(0.761)
D7	-1.118	-1.526	-0.794	-1.490	-2.821	-2.130	-2.820	-1.354	-3.076	0.643	2.353	2.641
	(0.474)	(0.333)	(0.612)	(0.586)	(0.302)	(0.386)	(0.258)	(0.610)	(0.212)	(0.760)	(0.327)	(0.228)
D8	-1.255	-3.290	-0.094	-2.532	-4.205	-2.546	0.363	-0.800	1.901	-1.931	-0.225	-2.197
	(0.495)	(0.060)	(0.957)	(0.276)	(0.077)	(0.244)	(0.910)	(0.777)	(0.497)	(0.473)	(0.934)	(0.387)
D9	0.499	0.240	1.701	1.198	1.554	2.205	-0.898	-0.329	1.756	1.994	3.733	1.610
	(0.802)	(0.903)	(0.390)	(0.652)	(0.528)	(0.368)	(0.755)	(0.906)	(0.534)	(0.639)	(0.392)	(0.690)
High	-2.288	-0.042	-0.203	-6.157	0.237	-1.006	-6.402	-2.486	-2.305	1.999	3.524	1.582
	(0.182)	(0.980)	(0.890)	(0.025)	(0.927)	(0.652)	(0.023)	(0.374)	(0.348)	(0.469)	(0.160)	(0.536)

Table W10. Performance of *Low-High* quintile portfolios based on past R^2 of synthetic funds grouped by style

This table reports the annualized performance (expressed as a percentage) of portfolios that invest following a strategy based on past R^2 of the artificial synthetic funds estimated solving the linear problem (2)-(5). Following Algorithm I, performance models 4F, 5F and 7F are applied to synthetic funds and daily factor returns from the previous two years. Synthetic funds are grouped according style. Within each style group they are grouped in quintiles based on past R^2. Portfolio *Low* consists of equally-weighted investing, over the next month, in the synthetic 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 synthetic 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 is estimated respectively by means of 4F, 5F and 7F models. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

	All sample 1990-2015			Subsample 1990-1997			Subsample 1998-2007			Subsample 2008-2015		
Style	4F	5F	7F	4F	5F	7F	4F	5F	7F	4F	5F	7F
Small Growth	1.591	2.606	3.778	-0.125	3.186	3.439	2.897	3.405	4.432	0.336	2.371	1.253
	(0.005)	(0.000)	(0.000)	(0.800)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.721)	(0.004)	(0.159)
Small Blend	5.780	5.788	6.305	8.203	10.792	9.864	5.812	5.343	5.092	2.887	3.777	2.854
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.001)	(0.003)
Small Value	7.893	8.225	8.213	13.006	13.455	12.684	6.007	6.557	5.727	5.266	6.163	5.446
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mid-Cap Growth	1.249	2.335	2.902	-0.342	3.338	2.841	2.917	3.714	3.996	0.436	2.161	1.115
	(0.007)	(0.000)	(0.000)	(0.648)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.558)	(0.009)	(0.099)
Mid-Cap Blend	6.190	5.519	7.600	13.920	15.001	14.414	4.976	3.527	5.714	1.617	2.608	2.787
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.043)	(0.004)	(0.001)
Mid-Cap Value	2.750	2.324	4.202	4.500	5.591	5.966	2.083	1.411	3.141	2.099	2.546	2.713
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.031)	(0.000)	(0.006)	(0.003)	(0.000)
Large Growth	0.506	2.141	1.052	0.045	1.391	0.900	1.355	3.399	1.754	0.765	2.036	1.122
	(0.212)	(0.000)	(0.003)	(0.948)	(0.003)	(0.180)	(0.048)	(0.000)	(0.003)	(0.198)	(0.000)	(0.017)
Large Blend	4.957	4.619	5.226	7.154	7.858	7.062	3.889	3.691	4.628	3.132	3.331	2.913
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Large Value	2.975	2.152	2.637	0.044	4.051	3.905	1.551	0.882	1.984	2.535	2.628	1.737
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.073)	(0.000)	(0.000)	(0.000)	(0.007)
Index	1.641	2.513	1.708	-0.177	1.202	0.919	1.691	2.595	1.918	2.036	3.092	1.023
	(0.001)	(0.000)	(0.000)	(0.740)	(0.015)	(0.033)	(0.048)	(0.003)	(0.003)	(0.007)	(0.001)	(0.049)

Table W11. Correlation between volatility, idiosyncratic volatility and $1-R^2$

This table shows the correlation between idiosyncratic volatility (s.e. regression) (IVOL) and volatility (s.d. return) (VOL) and $1-R^2$. Panel A shows the results for mutual funds and Panel B for stocks. The variables are estimated using daily returns and the 4F model for the whole of the sample period. The *p*-values in brackets are from a Student's t-test of the linear correlation coefficient.

	Panel A: Mutual funds		Panel B: Stocks	
	Idiosyncratic volatility (IVOL)	$1-R^2$	Idiosyncratic volatility (IVOL)	$1-R^2$
Volatility (VOL)	0.815	0.179	0.997	0.250
	(0.000)	(0.000)	(0.000)	(0.000)
Idiosyncratic volatility (IVOL)		0.602		0.315
		(0.000)		(0.000)

Table W12. Asset allocation and R^2

Panel A of the table shows the asset allocation of the mutual funds. It is defined as the average of the monthly weight (expressed as a percentage) invested in the nine classes of stocks according to the Morningstar Style-box. The panel also shows the asset allocation of mutual funds when they are grouped in quartiles according to the average of R^2 quintiles using the 4F model and the daily returns from the previous two years. Panel B shows the distribution of the weight (expressed as a percentage) of the stocks according to their average market capitalization and the Morningstar Style-box. The panel also shows the distribution when stocks are grouped in quartiles following the same previous criterion. Panel C shows the regression between the differences in weights for *Low-High* mutual funds and the *Low-High* stocks (*p*-values in brackets).

Panel A: Mutual funds

Style (%)	Small Growth	Small Blend	Small Value	Mid Growth	Mid Blend	Mid Value	Large Growth	Large Blend	Large Value
Mean	8.33	7.08	5.67	10.97	8.27	6.50	17.60	14.95	13.50
Low R^2 Q1	11.55	8.65	6.71	13.20	8.83	6.27	14.99	10.30	8.75
Q2	9.81	7.62	5.40	14.76	9.88	6.96	16.38	12.18	10.13
Q3	6.61	6.27	5.34	9.21	8.09	7.00	19.13	17.06	15.51
High R^2 Q4	4.60	5.46	5.14	5.57	5.81	5.63	20.52	21.57	21.07
Low (Q1+Q2) – High (Q3+Q4)	10.15	4.54	1.63	13.18	4.81	0.59	-8.29	-16.15	-17.70
Low (Q1) – High (Q4)	6.95	3.19	1.57	7.63	3.02	0.64	-5.53	-11.27	-12.32

Panel B: Stocks

Style (%)	Small Growth	Small Blend	Small Value	Mid Growth	Mid Blend	Mid Value	Large Growth	Large Blend	Large Value
Mean	3.40	4.25	6.54	5.46	7.11	9.27	16.80	19.78	27.41
Low R^2 Q1	22.62	25.65	36.55	6.25	3.84	5.09	0.00	0.00	0.00
Q2	15.18	13.29	16.64	10.45	9.70	12.09	18.70	3.52	0.41
Q3	7.45	9.21	12.68	12.36	12.97	9.42	14.03	11.38	10.50
High R^2 Q4	0.83	1.68	3.43	3.01	5.24	8.99	17.57	24.02	35.22
Low (Q1+Q2) – High (Q3+Q4)	29.53	28.05	37.09	1.32	-4.67	-1.22	-12.90	-31.89	-45.30
Low (Q1) – High (Q4)	21.79	23.96	33.12	3.24	-1.40	-3.90	-17.57	-24.02	-35.22

Panel C: Stocks explaining funds

Endogenous variable	Low (Q1+Q2) – High (Q3+Q4) Funds	Low (Q1) – High (Q4) funds
Intercept	-0.804	-0.679
	(0.754)	(0.676)
Low (Q1+Q2) – High (Q3+Q4) stocks	0.303	
	(0.014)	
Low (Q1) – High (Q4) stocks		0.256
		(0.009)
R^2	0.60	0.65

Table W13. Database coverage for a subsample of Small Value mutual funds

A subsample of small value mutual funds is formed by selecting the five funds with lower (higher) average of quintiles based on past R^2 and higher (lower) performance using the 4F model. Databases are NYSE, NASDAQ and AMEX common stocks from Morningstar and share codes 10 and 11 of common stocks from CRSP. Comparing the stocks in the funds' portfolio holdings and those in the databases, the table shows the average weight (expressed as a percentage) of the portfolio covered by each database.

	Low R^2			High R^2		
Stock market	Morningstar	CRSP	Diff.	Morningstar	CRSP	Diff.
NYSE	39.13	25.38	13.75	38.76	24.89	13.87
NASDAQ	33.49	14.49	19.00	40.86	12.60	28.26
AMEX	5.39	7.31	-1.92	6.71	5.18	1.53
Total	78.01	47.18	30.83	86.32	42.67	43.65

Table W14. Performance of low-high quintile portfolios based on past (previous two months) R^2

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 months. 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 months. 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. *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. *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*. 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.

Model	(1) Mutual funds	(2) French VW portfolios	(3) French EW portfolios	(4) French Industries portfolios	(5) Stocks	(6) VW stock portfolios	(7) EW stock portfolios	(8) Synthetic funds
Panel A. Sample 1990-06/2015								
4F	2.432	4.230	11.641	3.465	22.418	1.582	4.505	4.644
	(0.004)	(0.000)	(0.000)	(0.077)	(0.000)	(0.000)	(0.000)	(0.000)
5F	1.935	3.203	11.518	2.804	22.896	1.519	4.499	4.011
	(0.018)	(0.007)	(0.000)	(0.122)	(0.000)	(0.000)	(0.000)	(0.000)
7F	2.315	4.265	11.605	2.625	23.372	1.611	4.479	5.079
	(0.002)	(0.000)	(0.000)	(0.173)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B. Subsample 1990-1997								
4F	4.633	5.359	20.294	11.625	20.931	1.234	4.255	5.925
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
5F	4.649	4.820	18.893	11.334	18.215	1.158	4.193	7.364
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
7F	4.344	4.349	18.150	9.316	16.489	1.219	3.952	6.734
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Panel C. Subsample 1998-2007								
4F	3.619	5.814	9.326	0.697	21.110	1.963	4.522	4.933
	(0.006)	(0.006)	(0.001)	(0.832)	(0.000)	(0.000)	(0.000)	(0.000)
5F	2.766	5.065	10.407	1.438	22.214	1.909	4.455	3.373
	(0.043)	(0.011)	(0.000)	(0.634)	(0.000)	(0.000)	(0.000)	(0.003)
7F	3.469	5.795	9.064	-0.238	22.015	1.953	4.476	5.088
	(0.004)	(0.003)	(0.000)	(0.943)	(0.000)	(0.000)	(0.000)	(0.000)
Panel D. Subsample 2008-06/2015								
4F	-1.108	0.490	5.332	-0.853	22.139	1.395	4.686	1.417
	(0.363)	(0.775)	(0.027)	(0.782)	(0.000)	(0.001)	(0.000)	(0.165)
5F	-0.399	1.310	6.619	-0.841	23.188	1.780	4.853	2.748
	(0.708)	(0.432)	(0.005)	(0.778)	(0.000)	(0.000)	(0.000)	(0.005)
7F	-1.798	-0.536	4.999	-0.725	23.871	1.281	4.648%	1.736
	(0.065)	(0.725)	(0.029)	(0.801)	(0.000)	(0.001)	(0.000)	(0.033)

Table W15. Low-high quintile portfolios based on past (previous two years) R^2 incorporating the additional aggregate volatility (VIX) factor in performance models

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, an extended version of performance models 4F, 5F and 7F including additionally a factor for aggregate volatility, are applied to mutual funds and daily factor returns from the previous two years. Aggregate volatility is proxied by the daily differences in VIX index from the Chicago Board Options Exchange (CBOE). 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 the extended version of 4F, 5F and 7F models including the VIX factor, respectively. For the next columns, this procedure is repeated for other investments. *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. *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*. 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.

Model	(1) Mutual funds	(2) French VW portfolios	(3) French EW portfolios	(4) French Industries portfolios	(5) Stocks	(6) VW stock portfolios	(7) EW stock portfolios	(8) Synthetic funds
Panel A. Estimates of VIX factor								
4F+VIX	-1.07E-04	-5.56E-04	-4.45E-04	-6.27E-04	-3.62E-04	-8.07E-05	-2.87E-05	-1.43E-04
	(0.145)	(0.002)	(0.008)	(0.000)	(0.081)	(0.008)	(0.118)	(0.013)
5F+VIX	-1.47E-04	-5.99E-04	-5.41E-04	-6.07E-04	-5.32E-04	-7.47E-05	-3.67E-05	-1.25E-04
	(0.028)	(0.000)	(0.001)	(0.000)	(0.004)	(0.003)	(0.023)	(0.024)
7F+VIX	-1.10E-04	-5.68E-04	-4.21E-04	-6.12E-04	-2.81E-04	-6.43E-05	-2.48E-05	-1.02E-04
	(0.028)	0.000	(0.006)	(0.000)	(0.084)	(0.009)	(0.128)	(0.024)
Panel B. Annualized performance								
4F+VIX	1.539	4.208	12.349	-2.130	34.536	2.076	4.953	3.744
	(0.022)	(0.000)	(0.000)	(0.262)	(0.000)	(0.000)	(0.000)	(0.000)
5F+VIX	1.764	4.502	13.014	1.300	36.272	2.040	5.109	3.849
	(0.007)	(0.000)	(0.000)	(0.482)	(0.000)	(0.000)	(0.000)	(0.000)
7F+VIX	1.745	4.360	12.496	1.790	34.786	2.127	5.078	4.750
	(0.003)	(0.000)	(0.000)	(0.363)	(0.000)	(0.000)	(0.000)	(0.000)

Table W16. The role of fund costs

Panel A shows the average expense ratio (expressed as a percentage) of mutual funds grouped by the R^2 from the 4F model for the whole sample period. Panel B show the results of applying Algorithm I with performance model 4F to gross returns of mutual funds and 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 is estimated by means of 4F model. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator. Panel C shows the difference in performance (expressed as a percentage) between the results using mutual fund gross returns (Panel B of this table) and those using net returns (Table 1 of the main paper). Panel D shows the results when Algorithm I is applied using gross returns and the 4F model with the *ImS* additional factor. Panel E shows the difference in performance (expressed as a percentage) between the results using mutual fund gross returns (Panel D of this table) and those using net returns (Table 3 of the main paper).

Panel A: Average expense ratio according to R^2 over the whole period sample

	Low	Q2	Q3	Q4	High	Low-High
Expense ratio	1.52	1.44	1.36	1.21	0.98	0.54

Panel B: Performance of quintile portfolios of mutual funds using gross returns

	Low	Q2	Q3	Q4	High	Low-High
R^2	97.0	98.2	98.6	99.1	99.6	65.6
Performance	0.90	0.51	-0.35	-0.84	-0.95	1.85
	(0.148)	(0.357)	(0.485)	(0.044)	(0.001)	(0.006)

Panel C: Difference in performance using gross and net returns

	Low	Q2	Q3	Q4	High	Low-High
Diff. performance	1.27	1.20	1.16	1.07	0.82	0.45

Panel D: Performance of quintile portfolios of mutual funds using gross returns and incorporating the additional *ImS* (Idiosyncratic minus systematic) factor

	Low	Q2	Q3	Q4	High	Low-High
R^2	97.1	98.2	98.7	99.2	99.6	67.9
Performance	-1.31	0.88	2.07	2.41	0.54	-1.84
	(0.138)	(0.261)	(0.005)	(0.000)	(0.151)	(0.026)

Panel E: Difference in performance using gross and net returns and incorporating the additional *ImS* (Idiosyncratic minus systematic) factor

	Low	Q2	Q3	Q4	High	Low-High
Diff. performance	1.28	1.37	1.15	0.94	0.56	0.72

Table W17. Low-high quintile portfolios based on past (previous two years) R^2 incorporating the additional *ImS* (Idiosyncratic minus systematic) factor in performance models

This table reports the results of applying Algorithm I, with an extended version of performance models 4F, 5F and 7F including additionally the *ImS* factor. The *ImS* factor captures the relationship between past percentage of 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. For results in column (1), 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 the extended version of 4F, 5F and 7F models including the *ImS* factor, respectively. For the next columns, this procedure is repeated for other investments. *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. *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*. 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.

Panel A. Estimates of *ImS* factor

Model	(1) Mutual funds	(2) VW stock portfolios	(3) EW stock portfolios	(4) French VW portfolios	(5) French EW portfolios	(6) French Industries portfolios	(7) Synthetic funds
4F+ImS	0.12	0.08	0.08	0.31	0.50	0.26	0.11
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
5F+ ImS	0.11	0.07	0.08	0.28	0.49	0.28	0.07
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
7F+ImS	0.10	0.08	0.09	0.31	0.50	0.21	0.06
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Panel B. Annualized performance

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
4F+ImS	-2.57	-0.62	2.18	-6.73	-6.62	-7.68	-0.42
	(0.001)	(0.021)	(0.000)	(0.000)	(0.000)	(0.002)	(0.595)
5F+ImS	-2.22	-0.53	2.24	-6.21	-6.69	-10.43	1.18
	(0.009)	(0.046)	(0.000)	(0.000)	(0.000)	(0.000)	(0.194)
7F+ImS	-1.63	-0.61	2.12	-6.56	-6.47	-9.51	0.14
	(0.017)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.868)

Table W18. Comparing the performance of low-high quintile portfolios based on past R^2 of mutual funds and artificial portfolios

This table reports the difference between the annualized performance (expressed as a percentage) of *Low-High* quintile portfolio based on past R^2 of the mutual funds and artificial portfolios. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

Model	(1) VW stock portfolios	(2) EW stock portfolios	(3) French VW portfolios	(4) French EW portfolios	(5) French Industries portfolios	(6) Synthetic funds
Panel A. Sample 1990-06/2015						
4F	-0.66	-3.59	-2.09	-10.33	-0.78	-2.18
	(0.249)	(0.000)	(0.018)	(0.000)	(0.674)	(0.000)
5F	-0.38	-3.50	-2.26	-10.84	1.09	-2.13
	(0.502)	(0.000)	(0.006)	(0.000)	(0.536)	(0.000)
7F	-0.41	-3.43	-2.28	-10.39	0.63	-3.02
	(0.427)	(0.000)	(0.011)	(0.000)	(0.737)	(0.000)
Panel B. Subsample 1990-1997						
4F	0.68	-2.84	-2.00	-20.18	-6.26	-1.93
	(0.387)	(0.000)	(0.124)	(0.000)	(0.016)	(0.018)
5F	0.80	-2.49	-1.93	-19.60	-4.26	-3.74
	(0.299)	(0.001)	(0.092)	(0.000)	(0.086)	(0.000)
7F	0.48	-2.73	-0.81	-17.90	-3.91	-4.20
	(0.544)	(0.000)	(0.467)	(0.000)	(0.120)	(0.000)
Panel C. Subsample 1998-2007						
4F	1.07	-1.64	-1.44	-6.59	1.74	-0.55
	(0.212)	(0.090)	(0.313)	(0.003)	(0.585)	(0.407)
5F	1.19	-1.64	-2.00	-7.74	2.03	-0.28
	(0.173)	(0.094)	(0.130)	(0.000)	(0.507)	(0.700)
7F	1.48	-1.31	-1.55	-6.21	3.78	-1.23
	(0.054)	(0.123)	(0.260)	(0.002)	(0.236)	(0.038)
Panel D. Subsample 2008-06/2015						
4F	-3.81	-6.65	-2.32	-6.79	0.58	-3.48
	(0.000)	(0.000)	(0.079)	(0.001)	(0.845)	(0.000)
5F	-3.31	-6.09	-3.41	-8.20	2.00	-3.99
	(0.000)	(0.000)	(0.004)	(0.000)	(0.484)	(0.000)
7F	-4.00	-7.06	-1.34	-6.88	0.72	-4.17
	(0.000)	(0.000)	(0.295)	(0.001)	(0.803)	(0.000)

Table W19. Comparing the performance of *Low-High* quintile portfolios based on past R^2 of mutual funds (Table W8) and synthetic funds (Table W10) grouping by style

This table reports the difference between the annualized performance (expressed as a percentage) of the *Low-High* quintile portfolios that invest following a strategy based on past R^2 of the mutual funds (Table W8) and that corresponding to their counterpart artificial synthetic funds (Table W10). Funds are grouped according to style. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

	All sample 1990-2015			Subsample 1990-1997			Subsample 1998-2007			Subsample 2008-2015		
Style	4F	5F	7F	4F	5F	7F	4F	5F	7F	4F	5F	7F
Small Growth	-0.033	-2.422	-2.146	3.120	-2.607	-2.332	1.328	-0.933	-0.168	-3.288	-4.497	-4.240
	(0.970)	(0.005)	(0.009)	(0.103)	(0.159)	(0.136)	(0.315)	(0.498)	(0.880)	(0.008)	(0.000)	(0.001)
Small Blend	-4.273	-5.222	-4.650	-6.251	-12.148	-11.194	-2.921	-3.247	-1.992	-3.462	-3.732	-3.694
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.009)	(0.003)	(0.070)	(0.003)	(0.001)	(0.001)
Small Value	-4.964	-4.784	-4.863	-11.462	-12.056	-11.495	-0.949	-0.999	-0.170	-5.208	-5.105	-5.901
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.456)	(0.412)	(0.894)	(0.000)	(0.000)	(0.000)
Mid-Cap Growth	-0.593	-3.204	-1.278	4.993	-0.660	-0.355	-0.594	-2.971	-0.699	-3.350	-4.533	-3.252
	(0.603)	(0.006)	(0.205)	(0.035)	(0.750)	(0.858)	(0.764)	(0.146)	(0.673)	(0.004)	(0.001)	(0.002)
Mid-Cap Blend	-4.282	-4.080	-5.149	-7.392	-10.582	-11.474	-1.721	-0.580	-2.674	-4.116	-4.419	-3.230
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.238)	(0.699)	(0.027)	(0.000)	(0.001)	(0.016)
Mid-Cap Value	-1.984	-2.171	-3.582	-2.068	-5.519	-4.897	-0.324	-0.293	-1.680	-3.085	-2.483	-3.546
	(0.012)	(0.003)	(0.000)	(0.248)	(0.000)	(0.001)	(0.777)	(0.792)	(0.142)	(0.005)	(0.023)	(0.001)
Large Growth	0.684	-0.898	0.317	3.027	1.373	1.576	0.947	-1.161	0.874	-1.811	-2.420	-2.426)
	(0.253)	(0.125)	(0.612)	(0.001)	(0.098)	(0.113)	(0.373)	(0.229)	(0.408)	(0.012)	(0.004)	(0.002)
Large Blend	-4.144	-3.851	-4.302	-5.909	-6.374	-6.497	-2.310	-2.030	-2.562	-3.459	-3.646	-3.692
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Large Value	-1.903	-1.198	-1.748	-3.446	-3.375	-3.575	0.149	1.377	-0.032	-2.856	-3.038	-2.486
	(0.001)	(0.041)	(0.003)	(0.000)	(0.000)	(0.000)	(0.890)	(0.173)	(0.977)	(0.001)	(0.000)	(0.003)
Index	-1.274	-1.416	-1.878	0.693	1.090	0.572	-0.924	-1.465	-2.505	-1.807	-2.185	-0.643
	(0.075)	(0.044)	(0.008)	(0.649)	(0.486)	(0.713)	(0.372)	(0.099)	(0.013)	(0.085)	(0.075)	(0.546)

Table W20. Low-high quintile portfolios based on double sorting: past (previous two years) R^2 and loading on *ImS* (Idiosyncratic minus systematic) factor

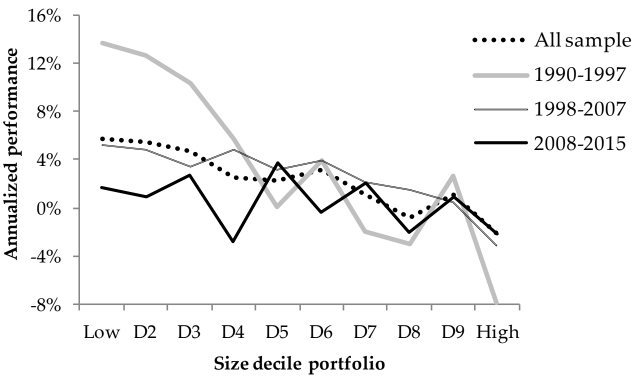
This table summarizes the results of applying a variant of Algorithm I, with an extended version of the performance model 4F including additionally the *ImS* factor and a double sorting based on past (previous two years) R^2 and loading on *ImS* (b_{ImS}). Panel A shows the results when applying the algorithm; firstly the portfolios are sorted in quintiles by past b_{ImS} and then, within each quintile they are ordered by past R^2. The results in the opposite direction are displayed in panel B. The first row shows the results for mutual funds. This procedure is repeated for other investments, so *VW* and *EW stock portfolios* are value (equally) weighted formed randomly from equities traded on the NYSE, AMEX and NASDAQ stock markets. *Synthetic funds* is a set of artificial portfolios estimated by solving the linear problem (2)-(5). For the *Low-High* past R^2 quintile portfolios: Subpanels 1A and 1B show the differences between the estimates of b_{ImS}; Subpanels 2A and 2B show the differences in annualized mean return (expressed as a percentage) and Subpanels 3A and 3B, the differences in annualized abnormal performance (expressed as a percentage) from model 4F and *ImS* factor. The *p*-value is from the Newey and West (1987) heteroskedasticity and autocorrelation consistent covariance estimator.

	Differences between *Low-High* past R^2 quintile portfolios										
	Panel A: Sorted first by past b_{ImS} and then by past R^2						Panel B: Sorted first by past R^2 past and then by past b_{ImS}				
	Low b_{ImS}	Q2	Q3	Q4	High b		Low b_{ImS}	Q2	Q3	Q4	High b_{ImS}
Subpanel A1						Subpanel B1					
Estimate of b_{ImS}											
Mutual funds	0.075	0.082	0.080	0.077	0.146		0.156	0.064	0.076	0.110	0.177
VW stock portfolios	0.049	0.042	0.043	0.038	0.051		0.077	0.075	0.075	0.077	0.078
EW stock portfolios	0.054	0.042	0.043	0.038	0.047		0.080	0.081	0.077	0.079	0.085
Synthetic funds	-0.036	0.052	0.075	0.092	0.165		0.091	0.085	0.085	0.106	0.194
Subpanel A2						Subpanel B2					
Annualized mean return											
Mutual funds	1.06	1.68	1.49	-0.22	-0.57		1.68	1.49	0.81	0.39	0.87
VW stock portfolios	2.06	1.76	1.94	1.98	1.86		1.91	1.94	2.09	1.92	2.25
EW stock portfolios	3.44	3.50	3.69	3.47	4.14		4.29	4.46	4.50	4.58	5.01
Synthetic funds	1.71	2.45	2.46	2.69	7.09		1.84	2.80	3.05	4.00	8.59
Subpanel A3						Subpanel B3					
Annualized performance											
Mutual funds	0.49	-0.93	-1.32	-2.76	-4.23		-1.77	-0.29	-1.71	-3.61	-5.12
	(0.632)	(0.360)	(0.074)	(0.000)	(0.001)		(0.081)	(0.743)	(0.056)	(0.000)	(0.000)
VW stock portfolios	0.17	0.15	0.32	0.59	0.05		-0.81	-0.67	-0.48	-0.72	-0.43
	(0.599)	(0.618)	(0.298)	(0.043)	(0.865)		(0.016)	(0.024)	(0.079)	(0.008)	(0.115)
EW stock portfolios	1.92	2.38	2.55	2.46	2.86		1.93	2.03	2.22	2.23	2.48
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Synthetic funds	3.17	-0.03	-1.04	-1.47	1.45		-1.15	-1.39	-1.13	-0.40	2.26
	(0.000)	(0.968)	(0.167)	(0.074)	(0.108)		(0.311)	(0.219)	(0.241)	(0.582)	(0.000)

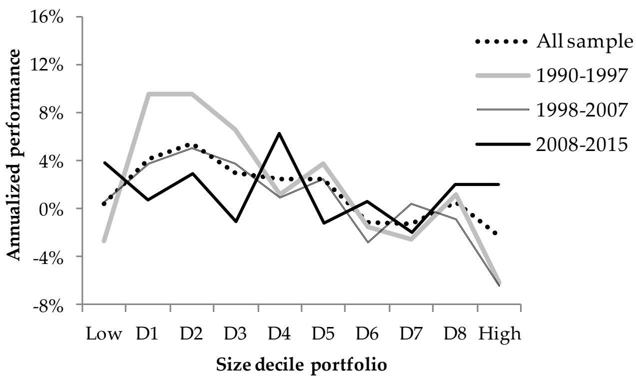
Figure W1. Performance of low-high quintile portfolios based on past R^2 of *French VW* and *EW* artificial portfolios grouped by size

This figure reports the values from Table W9 of 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 the sets of *French VW portfolios* and *French EW portfolios*. Following Algorithm I, using daily returns from the previous two years, performance models 4F, 5F and 7F are applied. Artificial portfolios are grouped in deciles according stocks size. Within each decile group artificial portfolios are grouped in quintiles based on past R^2. Portfolio *Low* consists of equally-weighted investing, over the next month, in the portfolios 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 portfolios 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 is estimated respectively by means of 4F, 5F and 7F models.

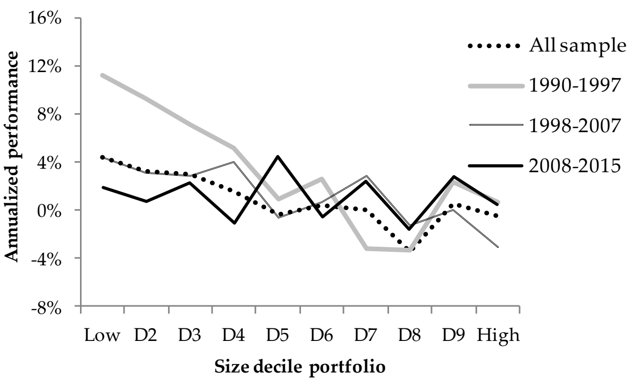
W1.a. *French VW portfolios*. 4F model.



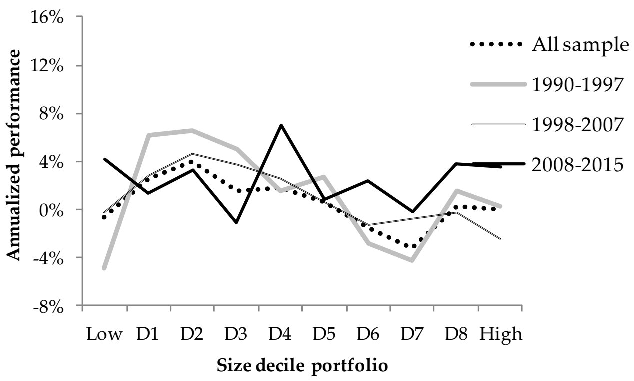
W1.d. *French EW portfolios*. 4F model.



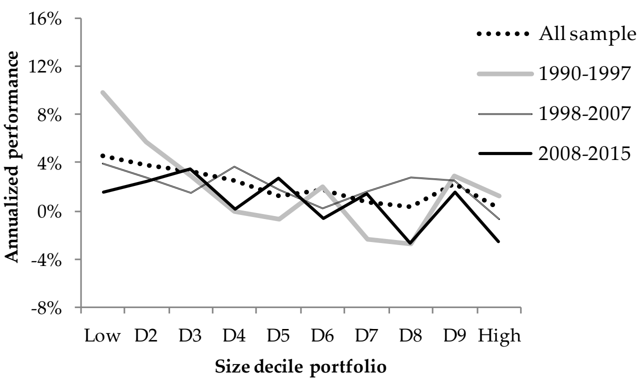
W1.b. *French VW portfolios*. 5F model.



W1.e. *French EW portfolios*. 5F model.



W1.c. *French VW portfolios*. 7F model.



W1.f. *French EW portfolios*. 7F model.