Mutual Fund's R^2 as Predictor of Performance

By

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This version: October 23, 2012

Forthcoming, ***Review of Financial Studies***

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We thank Martijn Cremers, Marcin Kacperczyk, Alex Kane, Antti Petajisto, Antonio Rubia (EFA discussant) and particularly two anonymous referees for helpful comments and suggestions. We also thank seminar participants at Erasmus University, McGill University, Society of Quantitative Analysis, Tilburg University, University of Toronto (Rotman), Waseda University (Tokyo), Wilfrid Laurier University, WHU (Koblenz) and EFA 2009 annual meeting. We thank William Goetzmann for providing us with mutual fund daily returns data; Martijn Cremers and Antti Petajisto for data on funds' Active Share and on benchmark index returns; Marcin Kacperczyk for data on Return Gap and Industry Concentration; and Russ Wermers for data on characteristic selectivity and characteristic timing measures.
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Abstract:
We propose that fund performance can be predicted by its R^2, obtained from a regression of its returns on a multi-factor benchmark model. Lower R^2 indicates greater selectivity and it significantly predicts better performance. Stock funds sorted into lowest-quintile lagged R^2 and highest-quintile lagged *alpha* produce significant annual *alpha* of 3.8%. Across funds, R^2 is positively associated with fund size and negatively associated with its expenses and manager's tenure.

Recent studies show that fund performance is positively affected by active management, measured by the deviation of funds holdings from a diversified benchmark portfolio (see review below). This measure of active management requires information on the portfolio composition of mutual funds and of their benchmark indexes, which are hard for many investors to obtain and calculate. In addition, the benchmark portfolio is not always accurately defined.

We propose an alternative intuitive and easily calculable measure of the active management in a mutual fund, which we term selectivity. This measure is derived from the fund's R^2, estimated by regressing its returns on returns of a multi-factor benchmark model. R^2 is the proportion of the fund return variance that is explained by the variation in these factors, thus lower R^2 means that the fund tracks them less closely. Selectivity is thus measured by $1\text{-}R^2$, the proportion of the fund's variance that is due to idiosyncratic risk or multi-factor tracking error. If selectivity enhances mutual fund performance, it should be negatively related to R^2.

We find that R^2 is a significant predictor, with a negative coefficient, of fund *alpha* (the excess return from a multi-factor model). This result is obtained even after controlling for fund characteristics, past performance and style. We also identify an R^2-based strategy that earns a significant positive risk-adjusted excess return. Sorting funds periodically into quintiles by their R^2 and *alpha*, we find that the portfolio with the lowest R^2 and highest *alpha* generates in the subsequent period a significant *alpha* of 3.804% or higher, depending on the benchmark factor model used.

Our results are robust to alternative factor models used as benchmarks. That is, our results are qualitatively similar for the Fama-French (1993) and Carhart (1997) four-factor model and for the four-factor model proposed by Cremers, Petajisto and Zitzewitz (2010) that uses common market indexes. This flexibility and versatility in the use of benchmark models is a beneficial property of R^2 as a measure of selectivity. We further demonstrate the versatility of our methodology by applying it to mutual funds that hold both corporate bonds and stocks. Using multi-factor models that include both stock and bond return factors, we again find that lower R^2 predicts higher *alpha*.

Some studies of fund selectivity or activity use fund holdings data. Brand, Brown and Gallagher (2005), Kacperczyk, Sialm and Zheng (2005), Cremers and Petajisto (2009, henceforth C-P) and Cremers, Ferreira, Matos and Starks (2011) show that active management – measured by the divergence of the fund portfolio composition (the portfolio weights of the stocks that it holds) from the composition of the fund's benchmark index – enhances fund performance. Daniel, Grinblatt, Titman and Wermers (1997) show that stocks that are picked by mutual funds outperform a characteristic-based benchmark with the gain being approximately equal in magnitude to the funds' management fee. Kacperczyk and Seru (2007) find that funds whose stocks holdings are related to company-specific information which differs from analysts' expectations exhibit better performance. Ferson and Mo (2012) use fund holdings data to develop mutual fund's investment performance measures.

Our analysis does not have such extensive data requirements. It does not require fund holdings data or knowledge of the fund's specific benchmark index. We use only returns data on funds and on benchmark indexes, all readily accessible, and our measure of a fund's strategy or selectivity – its R^2 – can be calculated easily.

We proceed as follows. Section 1 presents the predictor variable R^2 and the estimation procedure. Section 2 describes data and sample selection procedure. In Sections 3 to 7 we present tests of whether R^2 predicts fund's performance, using various measures of fund performance, followed by robustness tests. In Section 8 we present estimations of the association between fund characteristics on R^2. In Section 9 we extend the analysis to funds that invest in corporate bonds, showing that R^2 can predict their *alpha*. Concluding remarks are in Section 10.

1. R^2 as predictor of fund performance

We employ the benchmark model of factor-mimicking portfolios proposed by Fama and French (1993) and Carhart (1997) (denoted FFC) with return vectors *RM-Rf* (the market excess return), *SMB* (small minus big size stocks), *HML* (high minus low book-to-market ratio stocks) and *UMD* (winner minus loser stocks). We also employ as benchmark the model of Cremers, Petajisto and Zitzewitz (2010), denoted CPZC, which includes the excess return on the S&P500 index and the returns on the Russell 2000 index minus the return on the S&P500 index, the Russell 3000 value index minus the return on the Russell 3000 growth index, and the Carhart's (1997) momentum (*UMD*) factor. The results for this model are presented in an appendix on the *RFS* web site.

Fund performance is measured by $alpha_j$, the risk-adjusted excess fund return based on either the FFC or the CPZC factor model. We also use as performance measure the excess fund return measures of Daniel et al. (1997), named as the characteristic selectivity and characteristic timing components of return.

A regression of fund *j* returns on the benchmark factor returns produces R^2_j, which we propose as a predictor of fund performance. Selectivity is measured by

$$1 - R^2 = \frac{RMSE^2}{VARIANCE} = \frac{RMSE^2}{SystematicRisk^2 + RMSE^2} \ .$$

RMSE is the idiosyncratic volatility – the volatility of the residual from the above regression – and $SystematicRisk^2$ is the return variance that is due to the benchmark indexes' risk. Selectivity is greater if the fund's idiosyncratic volatility is higher *relative* to its total variance, meaning that the fund's volatility is less driven by factor-based (systematic) volatility. Studies of the predictive effect of *RMSE*-related measures show mixed results. C-P find that the fund tracking error, defined as the volatility of the return differential between the fund and its benchmark index, has an insignificant predictive effect on fund performance. Yet, Wermers (2003) finds better performance for funds with higher volatility of the S&P500-adjusted fund returns, which he uses as a measure of active management or selectivity. Our measure of selectivity, 1-R^2, is the weight of the tracking error with respect to a multiple-factor benchmark in the total return variance.[1]

Low R^2 could also arise from time-varying factor loadings (β) if fund managers time these factors at a higher frequency than we measure these βs, switching to high-β (low-β) securities when they expect high (low) market return. Below, we test the association between R^2 and measures of market timing and find that they are unrelated.

In what follows we estimate for each fund its R^2 in one period and test whether it predicts fund performance in the following period.

2. Data and Sample Selection

Our data sample spans the period 1988-2010. Data on fund monthly returns for this period are obtained from the CRSP Survivorship Bias Free Mutual Fund Database, which we merge with MFLINKS database available on WRDS. The CRSP returns are net after fees, expenses, and brokerage commissions but before any front-end or back-end loads. Data on fund characteristics are also obtained from the CRSP database. This database identifies each fund

[1]Recent studies of hedge fund use R^2 as a measure of factor exposure and find that low R^2 funds outperform high R^2 funds; see Titman and Tiu (2011) and Sun, Wang and Zheng (2011). However, hedge fund returns suffer from reporting biases, see Agarwal, Fos and Jiang (2010)

share class separately whereas MFLINKS tables assign each share class to the underlying fund. When a fund has multiple share classes on the CRSP database, we compute the weighted CRSP net returns, expenses, turnover ratio and other characteristics for each fund, the weights being the most recent total net assets of that shareclass.[2]

Our analysis includes actively managed equity funds whose investment objective codes, provided by Weisenberger and Lipper, are aggressive growth, growth, growth and income, equity income, growth with current income, income, long-term growth, maximum capital gains, small capitalization growth, micro-cap, mid-cap, unclassified or missing. When both the Weisenberger and the Lipper codes are missing, we use the Strategic Insight Objective Code to identify the style, and if the Weisenberger, Lipper and Strategic Insight Objective Code are all missing, we use investment objective codes from Spectrum, if available, to identify the style. If no code is available for a fund test period but the fund has the style identified for an earlier period, the fund is assigned for the missing test period the style from the previous period. If the fund style cannot be identified, it is excluded from the sample. We use nine style categories: (i) Aggressive Growth, (ii) Equity Income, (iii) Growth, (iv) Long term growth, (v) Growth and Income, (vi) Mid-Cap, (vii) Micro-Cap funds, (viii) Small cap, and (ix) Maximum Capital Gains. We eliminate index funds by deleting those whose name includes the word “index” or the abbreviation ind, S&P, DOW, Wilshire and Russell. We eliminate balanced funds, international funds (either by their stated style or by their name), sector funds and funds that hold less than 70% in common stocks. Following Elton, Gruber and Blake (1996) we require funds to have total net assets (*TNA*) of at least $15 million because inclusion of smaller funds may cause a survivorship bias problem due to reporting conventions. Addressing Evans’s (2010) comment on

[2] For funds with more than one share class we use monthly data on total net assets of each share class, available since 1991. Before it, we use the last available quarterly total net assets of each share class.

incubation bias, we eliminate observations before the fund's starting year reported by CRSP. We also require funds to have at least 70% of their assets in common stocks. And, following C-P, we delete funds with missing name in CRSP.

We set an estimation period of 24 months followed by a test period of one month (more details below).[3] In the estimation period we regress monthly fund excess return (over the one-month T-bill rate) on the FFC factor returns, moving this window a month at a time. This regression produces estimates of R^2 and *alpha* (the regression intercept) that are used to predict the fund's excess return in the test month that follows. Included in the sample for each test month are funds that have return data for the 24-month estimation period as well as data in the preceding month on all the control variables that may be associated with fund performance: *TNA*, Total Net Assets ($mm); *Expenses*, the expense ratio;[4] *Turnover*, defined as the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month *TNA* of the fund; *Fund Age*, computed as the difference in years between current date and the date the fund was first offered; and *Manager Tenure*, the difference in years between the current date and the date when the current manager took control.[5] The resulting distribution of the estimated R^2 is censored, 0.5% at each tail.[6] We end up with a sample of 237,290 observations for 2,460 funds.

INSERT TABLE 1

Table 1 includes statistics on the parameters and variables of interest. (This is also the sample that we use in the estimations presented in Table 4.) Estimated values of R^2 range

[3] The short estimation period accommodates Bollen and Busse's (2005) observation that funds' stock selection ability persists over a short period. Berk and Green (2004) propose that superior performance in mutual funds cannot persist even if it is a result of skill because it induces an inflow of funds which makes the fund grow in size and its performance to worsen because of decreasing returns to scale in fund management. Evidence on the positive performance-cash flow relation is presented by Kane et al. (1992).
[4] Expense ratio is the fraction of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees. The figures are reported quarterly.
[5] The manager can be an institution (asset management firm) with a long tenure.
[6] Funds with R^2 close to 1.0 are effectively "closet indexers" and very low R^2 may reflect outlier-type strategy or estimation error. Our results are similar if we winsorize the data instead.

between 0.529 and 0.994. The mean is 0.910 and the median is 0.929. This means that for most funds, over 90% of their return variability can be replicated by major stock indexes. The correlation table, Panel B of Table 1, shows that R^2 is higher for larger (high TNA) funds, which are likely to hold broader stock portfolios. Also, funds with lower R^2 have higher expense ratio. A detailed analysis of the determinants of R^2 appears in Section 8 and Table 6.

3. Fund portfolio performance based on sorting by lagged R^2 and *alpha*

We examine a strategy that predicts fund performance based on the fund's lagged R^2 and *alpha*. In each month *t*, we sort funds into five quintiles by their R^2_{t-1} and within each quintile we sort funds into five quintiles by their $alpha_{t-1}$. The sorting by $alpha_{t-1}$ is because of the evidence in Brown and Goetzmann (1995) and Gruber (1996) on persistence in fund's performance. Both R^2_{t-1} and $alpha_{t-1}$ are estimated by regressing monthly excess fund returns (over the T-bill rate) on the monthly FFC factor returns over 24 months preceding month *t*. This procedure produces 25 (5x5) portfolios with equal number of funds in each.[7] We require funds to have a defined style and a name on CRSP, have TNA_{t-1} > \$15 million and invest at least 70% of their assets in common stocks, all as of month *t*-1. We exclude index funds (those whose name includes the word "index" or the abbreviation "ind" or a name of a recognized index) and censor funds with extreme R^2_{t-1}, 0.5% at each tail. The sample includes 2,565 funds.[8]

For the test month *t* we calculate the average monthly excess returns (over the T-bill rate) of the funds that are included in each cell of Table 2 and these average excess returns are regressed on the FFC return factors over the twenty-one year period (252 months) 1990-2010. We present

[7] The number of fund months in each cell of the matrix may be slightly different because the number of funds in each month does not always divide exactly by 25.

[8] Because here we do not require funds to have other characteristics that are used in Tables 1 and 4, we include funds with missing data on these characteristics; consequently the sample here is slightly larger than that used for these tables.

for each portfolio the regression *alpha* (the regression intercept) and its *t*-statistic, using robust standard errors (following White, 1980).

INSERT TABLE 2

The results in Table 2 show in the row "All" that $alpha_t$ declines when moving from left (low R^2_{t-1}) to right (high R^2_{t-1}). That is, greater selectivity, measured by lower R^2, produces higher *alpha*. The annualized $alpha_t$ is 3.804% (t = 3.87) for the portfolio of funds in the lowest-quintile R^2_{t-1} and highest-quintile $alpha_{t-1}$, i.e., funds with the greatest selectivity and best past performance. For the portfolio with the lowest R^2_{t-1} and the second-highest $alpha_{t-1}$, the annualized $alpha_t$ is 1.697 (t = 2.18).

We test whether funds with low R^2_{t-1} significantly outperform funds with high R^2_{t-1} by estimating $alpha_t$ of a hypothetical portfolio of a long position in the lowest-R^2_{t-1} quintile funds and a short position in the highest-R^2_{t-1}-quintile funds for every $alpha_{t-1}$ quintile. The results are presented in the rightmost column of Table 2 under "Low-High." The return from this strategy is positive for all $alpha_{t-1}$ quintiles and on the whole, this strategy yields an annual $alpha_t$ of 2.052% (t = 2.68). For the highest and second-highest $alpha_{t-1}$ quintiles, this strategy yields an annual $alpha_t$ of 4.990% (t = 4.02) and 2.710 (t = 3.24), respectively.

We replicate this analysis using fund *gross* returns that measure fund managers' skill in selecting stocks before accounting for expenses (see Panel B of Table 2). Gross returns are calculated by adding back to the excess fund returns the monthly expenses (annual expenses divided by 12). The results, presented in Panel B, show again that performance is significantly better for low-R^2_{t-1} funds. The low-minus-high R^2_{t-1} portfolio has $alpha_t$ of 2.352% (t = 3.07). For the highest $alpha_{t-1}$ quintiles, the Low-High R^2_{t-1} strategy has $alpha_t$ = 5.375% (t = 4.33).

We re-estimate Table 2 using the CPZC factor model. The results (available on the *RFS* web site) are more significant, both economically and statistically. The estimated $alpha_t$ values are larger for the low R^2_{t-1} portfolios and for the Low-High R^2_{t-1} portfolios and their *t*-statistics are higher than those obtained for the FFC model.

Altogether, the results in Tables 2 demonstrate significant predictability in fund performance. Funds' risk-adjusted excess return is higher for funds with better past performance and greater selectivity, measured by $alpha_{t-1}$ and R^2_{t-1}, respectively.

4. Predicting fund performance measured by characteristics-based excess return (Daniel, Grinb1att, Titman and Wermers, 1997)

Daniel et al. (1997) propose two measures of fund performance: (i) "Characteristic Selectivity" (*CS*), the difference between the weighted average return of the previously disclosed fund stock holdings and the weighted average return on one of the 125 passive benchmark portfolios that is matched to each stock in the fund portfolio based on market capitalization, book-to-market and prior-year return, the weights being those of the stocks that constitute the fund's previously-disclosed holdings; (ii) "Characteristic Timing" (*CT*), the difference between the weighted return on the 125 characteristics portfolios in month *t* where the weights are those of the stocks with similar characteristics in the fund in month *t-1*, and the weighted return on the 125 characteristics portfolios in month *t* where the weights are those of the stocks with similar characteristics in the fund in month *t*-13. *CT* and *CS* "detect, respectively, whether portfolio managers successfully time their portfolio weightings on these characteristics and whether managers can select stocks that outperform the average stock having the same characteristics" (Daniel et al., 1997, p. 1035).

If R^2 is a measure of the fund manager's selectivity, it should predict performance based on *CS* but not necessarily performance based on *CT*. The data on monthly *CS* and *CT* are kindly provided by Russ Wermers, covering the periods 1990-2006 and 1994-2006, respectively. (The monthly returns are expressed in percent points and are multiplied by 12 to annualize them.) We estimate models with $CS_{j,t}$ as the dependent variable, predicted by $R^2_{j,t-1}$ and lagged fund characteristics that may affect the fund's performance:

$$CS_{j,t} = \gamma_t TR^2_{j,t-1} + \delta_{1t} Expenses_{j,t-1} + \delta_{2t} log(TNA)_{j,t-1} + \delta_{3t}[log(TNA)]^2_{j,t-1}$$
$$+ \delta_{4t} Turnover_{j,t-1} + \delta_{5t} log(Fund\ Age)_{j,t-1} + \delta_{6t} log(Manager\ tenure)_{j,t-1}$$
$$+ \sum_{n=1}^{9} \lambda_{nt} StyleDummy_{j,n,t-1} + e_t \ , \qquad (1)$$

A similar model is estimated with $CT_{j,t}$ as the dependent variable. The regression uses the logistic transformation of R^2, given that its distribution is negatively skewed with its mass being in the high values that are closer to 1.0 (which is its upper bound):

$$TR^2 = log[(\sqrt{R^2}+c)/(1-\sqrt{R^2}+c)] \ , \qquad (2)$$

where $c = 0.5/n$, n being the sample size.[9] The resulting distribution of TR^2 is more symmetric than that of R^2. We also present estimations of model (1) using untransformed R^2.

R^2 is estimated from the FFC model over 24 months preceding the test month and we employ the same sample selection criteria and data requirements that is used for Table 1. In the final sample that includes all the data, we censor the extreme 0.5% tails of the distribution of the estimated R^2 to eliminate outliers and closet indexers. The sample for the estimations using *CS* includes 149,546 observations and the sample for *CT* includes 136,833 observations.

Model (1) is estimated by the Fama-MacBeth (1973) procedure, following Carhart (1997) and Chen, Hong, Huang and Kubik (2004). For the $CS_{j,t}$ ($CT_{j,t}$) regressions, we estimate the

[9] This adjustment is suggested by Cox (1970, p. 33). Here, $n = 24$.

coefficient γ_t as well as the other coefficients over 204 (156) monthly test periods, 1990-2006 (1994-2006, respectively). The hypothesis is that $\gamma < 0$ in the model where $CS_{j,t}$ is the dependent variable. That is, lower R^2 indicates greater selectivity which enhances fund performance, measured by *CS*. If R^2 is not related to mutual fund timing strategies, we expect $\gamma = 0$ for the model where $CT_{j,t}$ is the dependent variable.

INSERT TABLE 3

Table 3, which presents the estimation results of Model (1), shows that R^2 significantly predicts *CS* with negative sign but it does not predict *CT*. For *CS*, the mean coefficient γ_t of TR^2_{t-1} is -1.374 with t = 2.95.[10] Because of variations over time in the standard errors of γ_t we follow Litzenberger and Ramaswamy (1979) and Ferson and Harvey (1999, Appendix A) and calculate the weighted mean of γ_t. The weights are inversely proportional to the standard errors of γ_t, i.e., more precise estimates are weighted more heavily. The weighted mean of γ_t is -0.874 (t = 2.64). When using $R^2_{j,t-1}$ (untransformed) as the explanatory variable in model (1), the mean γ_t is -9.679 with t = 2.87 and the weighted mean of γ_t is -6.549 (t = 2.72). The results thus show that $R^2_{j,t-1}$ is a significant predictor of fund performance, measured by Daniel et al.'s (1997) characteristic selectivity, $CS_{j,t}$.

Following C-P, we test whether the predictive effect of $R^2_{j,t-1}$ depends on fund size (*TNA*) by adding to model (1) an interaction variable $TR^2_{j,t-1}$**DUMsmall,* where *DUMsmall* = 1 if $TNA_{j,t-1}$ is below the median *TNA* for the month. C-P find that their measure *Active Share* predicts *CS* significantly only for below-median size funds (see their Table 9). We obtain that the mean coefficients of $TR^2_{j,t-1}$ and $TR^2_{j,t-1}$**DUMsmall* are, respectively, -1.297 (t = 2.76) and -0.129 (t = 1.80). The weighted means of the coefficients of $TR^2_{j,t-1}$ and $TR^2_{j,t-1}$**DUMsmall* are negative as well and their t-statistics are 2.44 and 1.89, respectively. When using $R^2_{j,t-1}$ instead of

[10] The serial correlation of the coefficients γ_t, 0.116, is statistically insignificant.

$TR^2_{j,t-1}$, the results are qualitatively similar. $R^2_{j,t-1}$ thus significantly predicts fund performance ($CS_{j,t}$) for *both* large and small funds, with a slightly stronger predictive power for smaller funds.

In contrast, when $CT_{j,t}$ is the dependent variable, the coefficient of $TR^2_{j,t-1}$ and of $R^2_{j,t-1}$ are insignificantly different from zero. While $R^2_{j,t-1}$ predicts fund performance associated with selectivity, it does not predict fund performance based on timing, measured by $CT_{j,t}$. This is consistent with R^2 being a measure of selectivity in fund management.

Independent support for the predictive power of R^2 is provided by Ferson and Mo (2012) who propose a measure of fund performance based on fund holdings data, which extends the measures of Daniel et al. (1997) by including a measure of volatility timing. The authors find that R^2 significantly predicts funds' total *alpha* while other predictive variables – C-P's Active Share and Kacperczyk et al.'s (2005, 2008) Industry Concentration Index and Return Gap (both discussed below) – have statistically insignificant effect on fund performance.

5. Predicting fund performance measured by *alpha*

We test whether $R^2_{j,t-1}$ predicts fund performance in month t measured by $alpha_{j,t}$. It is the difference between the fund excess return (over the one-month T-bill return) and the fund's predicted return, obtained by multiplying the factor returns in month t by the estimated factors' slope coefficients (β) from the preceding estimation period of 24 months (see, e.g., Cremers, Ferreira, Matos and Starks (2011), among others; *alpha* is expressed in percent (%) points and annualized by multiplying its monthly values by 12). In the cross-section model, $alpha_{j,t}$ is predicted by $TR^2_{j,t-1}$ and fund characteristics:

$$alpha_{j,t} = \gamma_t TR^2_{j,t-1} + \delta_{1t} Expenses_{j,t-1} + \delta_{2t} log(TNA)_{j,t-1} + \delta_{3t}[log(TNA)]^2_{j,t-1}$$
$$+ \delta_{4t} Turnover_{j,t-1} + \delta_{5t} log(Fund\ Age)_{j,t-1} + \delta_{6t} log(Manager\ tenure)_{j,t-1}$$
$$+ \delta_{6t} alpha_{j,t-1} + \sum_{n=1}^{9} \lambda_{nt} StyleDummy_{j,n,t-1} + e_t \quad (3)$$

The explanatory variables include $alpha_{j,t-1}$ (the regression intercept from the estimation period) which may reflect managerial skill and persistence in performance (see Brown and Goetzmann (1995) and Gruber (1996); we also report results for a model that excludes $alpha_{j,t-1}$).

Our hypothesis is that $\gamma < 0$. That is, $alpha_{j,t}$ is higher for funds with lower $R^2_{j,t-1}$, which indicates greater selectivity in investment. We estimate the coefficients γ_t as well as the other coefficients by the Fama-MacBeth (1973) method over 252 monthly test periods during the 21 year sample period 1990-2010. The sample is the one used in Table 1.

INSERT TABLE 4

The results in Table 4, Panel A support our hypothesis: the mean γ_t is negative, –1.045, and significant, t = 2.94.[11] The median is –0.711, and the proportion of negative coefficients is 144/252, significantly different from ½ ($p < 0.05$), thus rejecting the null hypothesis that this result is obtained by chance. We also calculate the weighted mean of γ_t to account for variation in its standard error over time. The weights are inversely proportional to the standard errors, thus giving greater weight to coefficients that are estimated more precisely. The weighted mean of the coefficient γ_t of TR^2 is -0.930 (t = 3.69).

When we exclude from model (3) the lagged fund performance $alpha_{j,t-1}$, the effect of $TR^2_{j,t-1}$ is more significant both economically and statistically. The mean γ_t becomes -1.331 (t = 3.67) with the proportion of negative coefficients being 150/252, significantly different from ½ (p <

[11] The serial correlation of γ_t, 0.12, is statistically insignificant. When we estimate the t-statistic by the Newey-West (1987) procedure with one lag we obtain that the t-statistic is 2.78.

0.01). This stronger effect of $TR^2_{j,t-1}$ is because $alpha_{j,t-1}$, which itself is affected by the fund's strategy and its R^2, absorbs part of the effect of $R^2_{j,t-1}$ on $alpha_{j,t}$.

When using the CPZC benchmark model to calculate *alpha* and R^2 in model (3), $TR^2_{j,t-1}$ has stronger predictive power. (Results are available on the *RFS* web site.) The mean γ_t is -1.235 (t = 3.47), the weighed mean is -1.189 (t = 4.62), and the proportion of negative coefficients is 151/252, significantly different from ½ which is the chance result ($p < 0.01$). As expected, the correlation between the estimated series γ_t for the two benchmark models, FFC and CPZC, is positive and quite high, 0.74. Again, if we exclude $alpha_{j,t-1}$ from model (3) the mean γ_t is more negative and significant: -1.650 (t = 4.50) with 155/252 of the coefficients being negative.

Next, we estimate model (3) with $R^2_{j,t-1}$ (untransformed) as explanatory variable (results are in Table 4). The mean coefficient γ_t of $R^2_{j,t-1}$ is -8.212 (t = 2.85) the weighted mean is -6.780 (t = 3.60), and the proportion of negative coefficients is 142/252, which is significantly different from ½, the chance result. Without $alpha_{j,t-1}$ in the model, the coefficient of $R^2_{j,t-1}$ is -10.481 (t = 3.58) and 148/252 of the coefficients are negative. The results are more significant, both economically and statistically, when using the CPZC benchmark model.

To illustrate the economic meaning of the estimated effect of $R^2_{j,t-1}$, consider two funds that are identical in all characteristics except that one has $R^2 = 0.9$ (which is roughly the mean) and the other has $R^2 = 0.8$. The coefficient of $R^2_{j,t-1}$, -8.212, means that the annualized *alpha* of the first fund will be lower by 0.821% than that of the second fund. Using the estimation result from the model that employs TR^2_{t-1}, where the coefficient is -1.045, we obtain that the difference in annualized *alpha* between the two funds is 0.646%.

The control variable $Expenses_{j,t-1}$ has a negative and significant coefficient and $alpha_{j,t-1}$ has a positive and significant coefficient. The coefficients of the other fund characteristics are statistically insignificant, including that of fund size (*TNA*), unlike the result in Chen et al. (2004).

The predictive power of R^2 holds for at least 6 months, as shown in Panel B of Table 4. The coefficient of $R^2_{j,t-1}$ is statistically significant for $alpha_{j,t+k}$, $k = 1, 2, \ldots 5$ (the results for $k = 0$ are in Panel A). Notably, the magnitude of the coefficients of R^2 or TR^2 and their statistical significance does not decline over the six-month prediction horizon.

Our testing procedure follows the Fama-Macbeth (1973) method with monthly cross-sectional regression. For robustness, we estimate model (3) by a single panel regression with fixed coefficients and with added time and style fixed effects. The standard errors are clustered by time and by fund. We obtain that the estimated coefficient of $TR^2_{j,t-1}$ is -1.105 with $t = 2.76$. When $alpha_{j,t-1}$ is excluded, this coefficient becomes -1.332 with $t = 3.23$. The results are more significant, both economically and statistically, when using the CPZC benchmark model.

As a robustness check, we replicate the analysis using *daily* returns data. We set sequences of 42 non-overlapping half-year test periods over the 21 sample years (1990-2010) during which we estimate $alpha_{j,t}$ (the regression intercept),[12] each being preceded by a half-year estimation period during which we estimate the fund's $R^2_{j,t-1}$ and $alpha_{j,t-1}$. The regressions employ current and one-day lagged returns (see Dimson (1979)).[13] We require that a fund has at least 120 days of returns in the estimation period and 50 days in the test period.[14] Data on daily fund returns for the period 1989 to 1998 are obtained from the International Center for Finance at Yale School of Management. These data include Standard and Poor's database of live mutual funds (previously

[12] We replicate this analysis with the test period $alpha_{j,t}$ being similar in spirit to that used in Table 4, i.e., the difference between the fund excess return and its conditionally expected return using current factor returns and factor loadings (β) from the estimation period. The differential daily return is averaged over the ½ year test period. The results then are that the mean γ_t is more negative and significant than that reported here. By this method there is no requirement for a minimum number of days in the test period, thus avoiding survivorship bias.
[13] Cremers et al. (2010, p. 36) find that estimation of fund performance is not harmed by using daily fund returns because the average staleness in fund return is likely to be close to the average staleness in benchmark index return.
[14] This may cause a problem of survivorship bias which is expected to be minor.

known as Micropal mutual fund data). The S&P data are not survivorship-bias free. These data are supplemented by a daily return database used by Goetzmann, Ivkovic, and Rouwenhorst (2001) and obtained from the Wall Street Web. For the years 1999 to 2010, we obtained data from the CRSP Survivorship Bias Free Mutual Fund Database. Having a sample with all the required data (including fund characteristics), we trim the extreme 0.5% of the estimated values of R^2. The final sample has 36,914 observations of semi-annual fund-periods for 2,447 funds. In this sample, the mean of $R^2_{j,t-1}$ is 0.897 and the median is 0.932 – both about the same as those obtained from monthly return estimates – with values ranging between 0.254 and 0.994.

We estimate model (3) by the Fama-MacBeth (1973) procedure over the 42 half-year test periods, where the values of the control variables are as of the end of the estimation period which precedes the test period. We obtain that the mean γ_t is -0.332 (t = 1.26), the median γ_t is -0.399 and the weighted mean of γ_t is -0.419 (t = 2.15). The proportion of negative coefficients is 31/42, which is significantly different from ½ ($p < 0.01$). Notably we obtain a very high *positive* estimate of γ_t, 7.134, for the second half of 2008 which is the financial crisis period (the collapse of Lehman Brothers). This coefficient is 21 times the (absolute) mean of γ_t and 4.4 standard deviations greater than the mean. We re-calculate the mean γ_t excluding symmetrically the extreme most positive and most negative estimates of γ_t. We obtain that the mean γ_t for the remaining 40 half-year estimates is -0.412 with t = 2.44 and the weighted mean of γ_t is -0.494 with t = 3.08. Testing whether γ_t is related to the market return, we regress the 40 semi-annual estimates of γ_t (excluding the two extreme tail estimates) on the half-year market excess return (over the compounded one-month T-Bill rate) and a constant. The coefficient of the market excess return is negative and quite insignificant (t = 0.52). When using the CPZC factor model we obtain that for all 42 semi-annual test periods the mean γ_t is -0.739 (t = 2.67), quite significant. The weighted mean is -0.782 (t = 3.84) and the proportion of periods with $\gamma_t < 0$ is 33/42, significantly different from ½ ($p < 0.01$). (The detailed results are available on *RFS* website.)

We conclude that the fund's R^2 is a significant predictor of its subsequent performance, measured by the fund's *alpha*.

6. Comparison with other predictors of fund performance

6.1. Active Share (Cremers and Petajisto, 2009)

R^2 and Active Share (*AS*), the sum of absolute deviations of the fund's stock holdings (weights) from those of its benchmark index portfolio, are both measures of fund activity or selectivity. Therefore, our result that R^2 significantly predicts fund performance is consistent with C-P's findings that *AS* is a significant predictor of fund performance, supported by the recent international evidence in Cremers, Ferreira, Matos and Starks (2011).

Each of these measures of fund activity has its advantages and they are not exactly the same. R^2 is easy to calculate, using readily available returns data on funds and on a set of benchmark indexes, while the calculation of *AS* requires data on funds' portfolio holdings and on the composition of their benchmark index. On the other hand, *AS* has an advantage over R^2 in that, as C-P point out (p.3340), "[I]t …requires no return history and can be determined at any point in time as long as we know the portfolio holdings."

One difficulty with *AS* is determining the fund's benchmark index (see C-P, p. 3340). The use of the self-declared benchmark index is problematic because, as Sensoy (2009, p. 25) remarks, "almost one-third of actively managed, diversified U.S. equity mutual funds specify a size and value/growth benchmark index in the fund prospectus that does not match the fund's actual style." C-P resolve this problem by calculating the fund's *AS* with respect to commonly-used nineteen indexes over their entire 24-year sample period and assigning the index that produces the lowest *AS* as that fund's benchmark. By this method, a fund's benchmark index may differ from its formally stated one and may vary over time.

Now, suppose that a fund whose stated benchmark is the S&P500 invests *passively* most of its assets in this index and the rest is invested *passively* in the Russell 2000 small-cap index, which generally outperforms the S&P500 index. This fund's *AS* will be positive, given that its portfolio deviates from its benchmark's portfolio, and thus it will be considered active while in fact it is a passive indexer. However, its R^2 will be close to 1, properly identifying this fund as an indexer. This fund will also outperform its benchmark, and thus this procedure will produce a positive *AS*-performance relation for both gross and net (after expenses) returns when performance is the excess return over the benchmark index. When performance is measured by *alpha* from a multi-factor model, this fund's *alpha* will be zero when using gross returns and negative when using net returns.

This discussion raises the question of what is meant by a fund being "active." If it means deviating from a single benchmark index, including passively investing in an index that is expected to outperform the benchmark index, then *AS* reflects fund activity properly while R^2 does not. But if active management means selecting *individual* stocks that outperform any passive index investing, R^2 captures that better than *AS*. Because R^2 is calculated with respect to *any* set of indexes that includes the index used to calculate *AS*, it is more powerful than *AS* in detecting funds that disguise as active while doing passive multi-index investing. Measuring active fund management by R^2 enables to exclude strategies that can be home-made by investors who invest passively in indexes.

For funds whose objective is investing in more than one asset class without committing to a fixed proportions, *AS* – being calculated with respect to a single index – cannot be used whereas R^2 can, provided that R^2 is estimated over a short period of time and the fund does not change its asset composition too frequently.[15]

Finally, *AS* and R^2 treat differently the return correlation between index stocks and stocks that replace them in the fund's portfolio. When an index stock is replaced by another stock, *AS* rises regardless of the correlation between the returns on these two stocks (e.g., regardless of whether the two stocks are from the same or different industries), whereas the change in the value of R^2 depends on this correlation. The question then is whether active management means deviation from the benchmark's stock composition or deviation from the characteristics of the stocks that comprise the index. Each measure answers this question differently.

We now study the relation between *AS* and R^2 and their predictive power. Data on *AS*, provided by C-P, enable us to predict fund performance over 204 months, from 01/1990 to 12/2006. As we do for R^2, *AS* (which is also bounded) undergoes logistic transformation, $TAS = log[(AS+c)/(1-AS+c)]$, and we censor the 0.5% tails of both R^2 and *AS*. There are 1,846 active equity funds with data on *AS* that satisfy our data requirements.

We calculate the cross-fund correlation between $R^2_{j,t}$ and $AS_{j,t}$ in each month t and average these correlations over the 204 sample months. This correlation is negative, as expected, with mean (median) of -0.45 (-0.46) and values ranging from -0.19 to -0.59. This means that while R^2 and *AS* are related measures of active management and selectivity, they each contain information about the fund's strategy that is not included in the other measure.

We estimate model (3) with $TAS_{j,t-1}$ as explanatory variable replacing $TR^2_{j,t-1}$ and obtain that its effect is positive and significant as obtained by C-P. The mean coefficient is 0.557 with t =

[15] See discussion of estimating funds' betas over short periods in Bollen and Busse (2005).

2.22. We then correlate the estimated coefficient series γ_t of $TAS_{j,t-1}$ with the coefficient series γ_t when $TR^2_{j,t-1}$ is the explanatory variable. The correlation between them is -0.48 and highly significant. This is expected since both variables capture the effect of selectivity or active management on fund performance.

INSERT TABLE 5

Finally, we estimate model (3) with *both* $AS_{j,t-1}$ and $R^2_{j,t-1}$ (or their logistic transformations) and with $alpha_{j,t-1}$ either being included or excluded. (C-P's cross-section estimation model includes lagged benchmark-adjusted return instead of $alpha_{j,t-1}$.) The results, presented in Table 5, show that the negative effect of $TR^2_{j,t-1}$ or $R^2_{j,t-1}$ remains statistically significant. The effect of $AS_{j,t-1}$ is positive, as predicted, being more statistically significant when $alpha_{j,t-1}$ is excluded from the model. When using the CPZC factor model, the coefficient of $R^2_{j,t-1}$ is more negative with greater statistical significance and the coefficient of $AS_{j,t-1}$ is more positive and more significant. (These results are available on the *RFS* website).

We conclude that R^2, our measure of selectivity, provides significant contribution to the prediction of mutual fund performance in addition to that provided by *Active Share*.

6.2. Industry Concentration Index (*ICI*) and Return Gap (*RGap*) (Kacperczyk, Sialm and Zheng, 2005, 2008)

Kacperczyk et al. (2005) propose that fund performance is an increasing function of the fund's activity, measured by the industry concentration index (*ICI*), the sum of the squared deviation between the fund's weights of holdings in various industries and the weights of these industries in the market portfolio. Kacperczyk et al. (2008) propose another predictor of fund performance which measures managerial skill: the fund managers' unobserved actions as measured by the return gap (*RGap*), the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings.

We estimate model (3), adding lagged *ICI* or *RGap* as predictors and find that the coefficient of TR^2 remains negative and statistically significant in the presence of *ICI* and *RGap*. (The results are presented in the Appendix Table A1.)

7. Robustness tests: Is the effect of R^2 obtained due to pricing of volatility or mechanically?

The negative relation between $alpha_{j,t}$ and $R^2_{j,t-1}$ could be spurious rather than being a result of selectivity. It could result from equilibrium pricing of the variance components of R^2, or it could be obtained mechanically. We define $alpha = r - F\hat{b}$, where r is the vector of fund excess returns, F is the matrix of factor returns and $\hat{b}$ is the vector of estimated factor coefficients (β) obtained from the preceding estimation period. Since $R^2 = b'F'r(r'r)^{-1}$, regressing *alpha* on R^2 may result in a mechanical relation between γ, the estimated coefficient of R^2, and the values of the matrix F (the factors' returns).

We conduct three tests of robustness. The first test replicates the procedure employed in estimating Table 4 on Fama and French's 100 (10x10) portfolios sorted by size and by book-to-market ratio and on 48 industry portfolios. These portfolios can be viewed as passive mutual funds with constant and mechanical investment strategies. As in Table 4, we do cross-section Fama-MacBeth regressions of the test month's $alpha_{j,t}$ on $TR^2_{j,t-1}$ and on $alpha_{j,t-1}$ (and a constant).[16] We obtain that for both sets of portfolios, the coefficients of $TR^2_{j,t-1}$ or of $R^2_{j,t-1}$ are *positive* rather than negative and they are insignificantly different from zero (their *t*-statistics are all below 1.0). This suggests that the predictive effect of R^2 on fund performance that we find for

[16] In the regressions using the Fama-French 100 portfolios we emulate fund styles by adding dummy variables for small firms and for high and low book-to-market portfolios (indicating value and growth styles).

actively-managed funds is not a mechanically-obtained result. (The results are presented in Appendix Table A2.)

In the second test of robustness, we regress the monthly estimate of γ_t, obtained from Model (3) (and whose statistics are presented in Table 4), on the monthly FFC factor returns and a constant. The test is whether the constant is negative and significant after accounting for the effects of the factors on the estimated γ_t. We obtain that while the factor coefficients in this regression are negative – although only the coefficient of *RM-Rf* is significant – the intercept is still negative and statistically significant and its magnitude is close to the mean values of γ_t in Table 4, Panel A. For example, in a regression of γ_t on a constant and *RM-Rf*, the intercept is -0.868 with t = 2.52. (The results are presented in Appendix Table A3.) When excluding the second half of 2008 – the crisis period during which Lehman collapsed and the market crashed – the intercept is -1.046, with t = 3.01.

In the third robustness test we replicate the procedure in Table 2, Panel A, where we estimate the *alpha* (the intercept) from a regression of fund portfolio excess returns on the FFC factors returns. Here, instead of using fund returns we use as dependent variable the fund's monthly series of $alpha_{j,t}$ which is the dependent variable used in model (3). The results are qualitatively similar to those presented in Table 2 for fund excess returns. For example, for the highest-$alpha_{j,t-1}$ quintile, the fund portfolio with the lowest $R^2_{j,t-1}$ has *alpha* = 3.116% (t = 3.49) compared with *alpha* = 3.804% (t = 3.87) in Table 2. The low-minus-high $R^2_{j,t-1}$ portfolio has *alpha* = 3.637% (t = 4.42), compared with *alpha* = 4.990% (t = 4.02) in Table 2. In general, the *alpha* of the low-minus-high $R^2_{j,t-1}$ portfolio is 1.212% with t = 2.54.

We conclude that the negative relation between $R^2_{j,t-1}$ and fund performance measured by $alpha_{j,t}$ remains negative and highly significant after accounting for the attenuating effects of the factor returns on this relation.

8. The determinants of funds' R^2

Funds appear to choose a strategy, such as the extent of selectivity that we measure by R^2, which subsequently affects their performance. We now examine the effects of fund characteristics on its R^2 by regressing $TR^2_{j,t}$ on the lagged fund characteristics that are used in Model (1). Because $R^2_{j,t}$ is estimated over 24 months we use here 10 non-overlapping periods of 24 months from 1991 to 2010. The fund characteristics are as of the end of the year before the beginning of the 24-month estimation period. The effects of fund characteristics on $TR^2_{j,t}$ are estimated by a panel regression with time dummy variables; the standard errors are clustered by time and by fund.

INSERT TABLE 6

The results in Table 6 show that a fund's R^2 is related to some fund characteristics and styles. The coefficient of *Expenses* is negative and significant suggestion that high selectivity (lower R^2) is associated with higher expenses. This may be because higher selectivity incurs higher cost (e.g., in the acquisition and analysis of information) and because investors may be willing to pay more for funds with greater selectivity which have better performance since it is harder for them to replicate on their own the strategies of such funds. The negative coefficient of *Managerial Tenure* is consistent with Chevalier and Ellison's (1999, p. 391) suggestion that younger managers tend to herd or "avoid unsystematic risk when selecting their portfolio." Here it means that managers with shorter tenure choose higher-R^2 strategies, which causes a greater proportion of the fund risk to be systematic.

R^2 is an increasing and concave function of fund size (in logarithm), as evident from the positive and negative coefficients of *log(TNA)* and of $[log(TNA)]^2$, respectively. A larger fund increases its breadth because concentrating its investments in a few stocks causes liquidity problems when it needs to liquidate them (see discussion in Amihud and Mendelson, 2010). The higher R^2 for larger funds implies lower subsequent performance. This is consistent with Berk and Green's (2004) suggestion that performance-chasing investors make successful funds grow in size which in turn erodes their performance. Also, a positive TR^2-*TNA* relation may reflect the strategy of managers who derive utility from being more highly ranked in terms of fund size (Koijen, 2008). Managers of smaller funds who wish to improve their status by increasing their fund size have an incentive to "deviate from the pack" and employ idiosyncratic investment strategies (see Krasny, 2012). This means that the smaller fund managers would choose strategies that result in lower R^2, leading to a positive relation between *TNA* and R^2.

Fund *Turnover* has an insignificant coefficient, suggesting that greater selectivity in the formation of the fund's portfolio is not associated with more frequent trading. The negative coefficient of *Fund Age* (though its statistical significance is low) suggests that older funds are more active and more selective, which in turn enhances their performance and contributes to their longevity.

As a robustness check, we re-estimate the model using the Fama-MacBeth method. Then, the coefficients of *Expenses*, *log(Tenure)*, *log(TNA)* and $log(TNA)^2$ retain their sign and statistical significance and that of *Fund Age* remains negative and becomes significant at the 10% level.

We also observe R^2 is significantly related to fund styles. Funds that invest in *Micro-Cap* and *Mid-Cap* stocks and *Aggressive Growth* funds (the default style) have lower R^2, while growth funds (*Growth and Income, Growth and Long term growth*) as well as small-cap funds have relatively high R^2.

Having suggested that lower R^2 implies greater selectivity by fund managers, we now test whether lower R^2 also reflects the application of market timing strategy. This strategy implies investing more (less) in high-β securities when the market return is expected to be high (low, respectively). This would lower R^2 which is estimated from a fixed-coefficients model. To test that, we add to the basic FFC model market (from which we estimate R^2) timing-related variables that have been used in two earlier studies (e.g., Bollen and Busse, 2001, 2005): RM_t^2 (see Treynor and Mazuy, 1966), or I_t*RM_t where $I_t = 1$ if $RM_t > 0$ and $I_t = 0$ otherwise (see Henriksson and Merton, 1981). RM_t is the value-weighted CRSP market. A positive coefficient on either RM_t^2 or I_t*RM_t, which we respectively denote by β_1^{Timing} and β_2^{Timing} implies that the fund engages in market timing, i.e., it raises its market-return β when the market rises. If timing strategy lowers R^2, we expect a negative cross-section relation between R^2 and β_1^{Timing} or β_2^{Timing}.

Adding β_1^{Timing} or β_2^{Timing} to the regression model of Table 6 we obtain that the coefficients of these timing βs are positive and statistically insignificant. The coefficient of β_1^{Timing} is 0.003 with $t = 0.75$, and the coefficient of β_2^{Timing} is 0.017 with $t = 0.56$. Thus, there is no evidence that a fund's lower R^2 reflects market timing.[17] This is consistent with our results in Section 4 and Table 3 that R^2 does not predict the fund's performance due to timing.

[17] Interestingly, Elton et al. (2009) find that application of market timing worsens rather than improves fund performance.

9. Corporate bond funds: predicting *alpha* with R^2

We now analyze open-end mutual funds that invest in domestic corporate bonds in addition to their investment in stocks. Our methodology enables to evaluate the selectivity-related performance of such funds using benchmark factor models that include both stocks and bonds benchmark indexes. The first model, following Bessembinder et al. (2008), includes the three Fama-French (1993) factors (*RM-Rf*, *SMB* and *HML*) and two bond-spread factors: *DEF*, the difference between the return on BAA-rated bonds and AAA-rated bonds and *TERM*, the difference between the return on Treasury 30-year bonds and the 3-month Treasury bill rate. The bond data are the Lehman\Barclays series, obtained from Datastream. The second model, following Elton et al. (1995), includes the stock market excess returns (using CRSP value-weighted market return), the aggregate bond market returns (using Barclays US Aggregate Bond index, source: Datastream) and two return spread factors, *DEF* (as defined above) and *OPTION*, the return spread between the Barclays GNMA index and the Barclays Government Intermediate index (source: Datastream). The analysis is over the period 2001-2010 for which daily returns data are available for the benchmark factors.

The sample of funds includes those that have invested in corporate bonds at least 35% of their net asset value. This accommodates "Balanced Funds"[18] which are excluded from the analysis of stock funds. We exclude funds whose style indicates that they are Treasury, government or municipal bond funds.

The procedure is similar to that employed for stock mutual funds using daily return data. For each test period of half year t and for each fund j we estimate $alpha_{j,t}$, the intercept from the a

[18] Balanced Funds are defined in the CRSP manual as follows: "Funds whose primary objective is to conserve principal by maintaining at all times a balanced portfolio of both stocks and bonds. Typically, the stock/bond ratio ranges around 60%/40%."

regression of the fund excess return on the factors returns,[19] and we estimate $R^2_{j,t-1}$ and $alpha_{j,t-1}$ from such regressions over the preceding half-year data. The regressions employ the current day and two days lags, following Dimson (1979), to account for the slower adjustment of bond prices. We then estimate the cross-section model (3) by the Fama-MacBeth method over the 20 half-year test periods and calculate the statistics for the resulting estimated coefficients of each variable. As before, we require at least 120 daily returns in the estimation period and 50 daily returns in the test period, *TNA* > $15 million and availability of data for the variables in model (3). The estimated $R^2_{j,t-1}$ is censored by 0.5% in both tails. We obtain 1,334 observations of pairs of half-year fund periods.

In our sample, the average proportion invested in corporate bonds is 69.5% and median is 73.5%. The first and third quartiles of the proportion invested in bonds are, respectively, 49.4% and 88.0%, which means that nearly three quarters of the sample funds have at least 50% of their holdings in corporate bonds.

The mean (median) R^2 of the funds in the sample which uses the model of Bessembinder et al. (2008) is 0.53 (0.50), ranging between 0.165 and 0.985. When using the model of Elton et al. (1995), the mean (median) R^2 is 0.46 (0.44). These means and medians are lower than those for stock funds, perhaps because the investment strategies of many bond funds are not well captured by these factor models.

We estimate model (3) where $alpha_{j,t}$ is explained by $TR^2_{j,t-1}$, the transformed value of lagged R^2_j, and by the other control variables including 9 style dummy variables.[20] The results in

[19] We also do the analysis using $alpha_{j,t}$ as the average of the difference between the current fund excess return and the conditional expectation of the fund return, using current factor returns and estimated factor loading from the preceding period. The results are qualitatively the same as those presented here.

[20] The styles are: Corporate Debt A Rated, Corporate Debt BBB-Rated, Intermediate Investment Grade Debt, Short-Term Investment Grade Debt and Short-Intermediate Investment Grade Debt, High Current Yield, Balanced, General Bond, Income (including flexible and multi-sector) , and Flexible Portfolio..

Table 7 show that $TR^2_{j,t-1}$ is a significant predictor of performance for the two benchmark models. For the model of Bessembinder et al. (2008), the mean value of γ_t (the coefficient of $TR^2_{j,t-1}$) is -0.921 with t = 4.18. The median is -1.028 and the weighted mean is -0.856 (t = 4.87). The proportion of negative coefficients is 16/20, rejecting the null hypothesis that the proportion is ½ ($p < 0.01$). Employing the benchmark model of Elton et al. (1995) we obtain that the mean coefficient of $TR^2_{j,t-1}$ is -1.048 with t = 2.58, and the weighted mean coefficient is -0.818 with t = 4.26.

INSERT TABLE 7

We re-estimate the model using $R^2_{j,t-1}$ instead of $TR^2_{j,t-1}$. For the model of Bessembinder et al. (2008), the mean γ_t is -3.881 (t = 4.39) and the weighted mean is -3.547 (t = 4.74). The median is -3.926 and 16 of the 20 coefficients are negative, significantly different from ½ ($p < 0.01$). For Elton et al.'s (1995) benchmark model, the mean γ_t is -4.147 (t = 2.65) and the weighted mean is -3.047 (t = 3.99). Here, the proportion of negative coefficients is 14/20, in which case we reject the null that the proportion is not ½ at $p < 0.06$. Notably, the coefficients of TR^2 for bonds is slightly smaller than it is for stocks, and the coefficient of R^2 for bonds is about half the magnitude than it is for stocks.

As in the estimates of Table 4 for stocks, $alpha_{j,t-1}$ is a significant predictor of fund performance. The coefficient of $Expenses_{j,t-1}$, while still negative, is statistically insignificant. The coefficients of the other fund characteristics are also statistically insignificant, as is the case for stock funds.

The results thus show that for both benchmark models, R^2 predicts performance for mutual funds that include corporate bonds.

10. Conclusion

We propose an intuitive and convenient measure of mutual fund selectivity or activity: the R^2 from a regression of the fund return on multi-factor models that are commonly used as benchmarks for fund performance. Lower R^2 means a greater deviation of the fund's return from that of common factors, indicating greater activity or selectivity in the fund's investment. We find that funds with lower R^2 have subsequently higher risk-adjusted excess return (*alpha*) after controlling for fund characteristics and past performance. And, sorting stocks by their past R^2 and *alpha* into 25 (5x5) fund portfolios we find that the lowest-R^2 and highest-*alpha* portfolio produces an *alpha* of 3.8% or more (depending on the benchmark factor model used).

R^2 is found to be related to fund characteristics such as fund size, expenses, manager tenure, and style, which explain nearly 40% of the cross-fund variation in its values. This suggests that the strategy which is measured by R^2 is relatively stable and indeed we find evidence of persistence in funds' R^2 from one period to the next.

Our method of predicting fund performance by its lagged R^2 also holds for mutual funds that invest in corporate bonds. This demonstrates the flexibility of our measure, which can be applied for funds with any set of benchmark indexes.

Altogether, this study offers a new and convenient way to predict mutual fund performance using only their return data.

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Table 1. Summary Statistics on actively managed equity mutual funds

Panel A: Statistics for our sample of funds. R^2 and *alpha* are both estimated from regressions of fund returns (in excess of the one-month T-Bill rate) on the returns of the Fama-French (1993) and Carhart (1997) factor model (FFC) over a window of 24 months. This estimation period moves one month at a time, preceding the 252 one-month test periods that span the years 1990-2010. (*alpha* is multiplied by 1200 to annualize it.) The fund characteristics are as of the end of each 24-month estimation period. *Age* is the number of years since the fund was first offered. *Expenses* is the annual expense ratio. *Turnover* is the minimum of aggregated sales or aggregated purchases of securities divided by the average 12-month *TNA* of the fund. *Manager Tenure* is the number of years since the current manager took control. We use CRSP fund returns that are net of expenses. Data are for actively-managed equity funds that satisfy the sample selection requirements. There are 237,290 observations for 2,460 funds.

Panel A: Fund characteristics

	Mean	Median	Minimum	Maximum
TNA (total net assets, in $millions)	1,425.34	276.80	15.0	202,305.80
Fund Age (years)	13.621	9.39	2.00	86.33
Expenses (%)	1.237	1.20	0.01	5.32
Turnover (%)	85.19	65.00	0.0	4,550
Manager Tenure (years)	6.96	5.58	0.01	63.83
R^2	0.910	0.929	0.529	0.994
alpha (annualized, in %)	-0.818	-0.981	-45.611	80.666

Panel B: Cross-sectional correlations

The contemporaneous correlations for the control variables are estimated for the sample of monthly fund returns. * denotes significance at the 5% level.

	Log(TNA)	*Log (Fund Age)*	*Expenses*	*Turnover*	*Log(Manager Tenure)*	R^2
log(Fund Age)	0.381*					
Expenses	-0.318*	-0.210*				
Turnover	-0.124*	-0.102*	0.170*			
Log(ManagerTenure)	0.176*	0.303*	-0.104*	-0.171*		
R^2	0.136*	0.084*	-0.175*	-0.058*	-0.0002	
alpha	0.086*	-0.044*	-0.060*	-0.036*	0.022*	-0.134*

Table 2. Fund portfolio *alpha*, based on sorting on lagged R^2 and *alpha*

The table presents the portfolio *alpha*, annualized, using monthly returns. Portfolios are formed by sorting all funds every month into quintiles by R^2 and then by *alpha*. Both are obtained for the 24-month estimation period (*t-1*) by regressing each fund's monthly excess returns (over the T-bill rate) on the factors returns, using the FFC (Fama and French (1993) and Carhart (1997)) factor model. Then, for the following month test period (*t*) we calculate the monthly average excess returns for each portfolio of funds. The process repeats by moving the estimation and test period one month at a time. The test period average portfolio returns are regressed on the returns of the FFC model. For each portfolio (cell) we present *alpha*, the intercept from the above regression and its *t*-statistic, using robust standard errors (White (1980)). The sample period of the test months is from 1/1990 to 12/2010 (252 months). ***, **, * denotes significance at the 1%, 5% or 10% level.

Panel A. Results using *net* returns

	R^2_{t-1}						
$Alpha_{t-1}$	Low	2	3	4	High	**All**	**Low-High**
Low	-1.548 (1.57)	-1.606* (1.78)	-2.319*** (2.95)	-2.625*** (3.83)	-2.451*** (4.17)	-2.164*** (3.02)	0.903 (0.93)
2	-0.453 (0.51)	-0.867 (1.10)	-1.455** (2.40)	-1.273** (2.32)	-1.623*** (3.54)	-1.228** (2.44)	1.170 (1.36)
3	-0.472 (0.63)	-0.679 (0.91)	-0.471 (0.85)	-1.223** (2.54)	-1.019** (2.41)	-0.786* (1.78)	0.547 (0.68)
4	1.697** (2.18)	-0.213 (0.35)	-0.448 (0.60)	-1.051* (1.86)	-1.012** (2.47)	-0.527 (1.09)	2.710*** (3.24)
High	3.804*** (3.87)	0.720 (0.96)	-1.014 (1.21)	-0.716 (0.77)	-1.186 (1.52)	0.776 (1.11)	4.990*** (4.02)
All	0.595 (0.85)	-0.533 (0.87)	-1.137** (2.13)	-1.387*** (2.78)	-1.461*** (3.36)	-0.785* (1.70)	2.052*** (2.68)
High-Low	5.352*** (4.49)	2.326** (2.28)	1.305 (1.25)	1.909* (1.92)	1.265* (1.70)	2.940*** (3.28)	

Panel B. Results using *gross* returns

	R^2_{t-1}						
$Alpha_{t-1}$	Low	2	3	4	High	**All**	**Low-High**
Low	-0.104 (0.11)	-0.256 (0.28)	-1.039 (1.32)	-1.348** (1.97)	-1.242** (2.12)	-0.838 (1.17)	1.138 (1.18)
2	0.879 (0.99)	0.409 (0.52)	-0.232 (0.38)	-0.106 (0.19)	-0.529 (1.16)	-0.026 (0.05)	1.408 (1.63)
3	0.834 (1.11)	0.558 (0.75)	0.712 (1.29)	-0.085 (0.18)	0.012 (0.03)	0.366 (0.83)	0.821 (1.02)
4	3.009*** (3.87)	1.024* (1.67)	0.725 (0.98)	0.061 (0.11)	-0.033 (0.08)	0.622 (1.29)	3.042*** (3.65)
High	5.194*** (5.28)	1.994*** (2.66)	0.217 (0.26)	0.458 (0.49)	-0.179 (0.23)	2.032*** (2.92)	5.373*** (4.33)
All	1.951*** (2.78)	0.741 (1.21)	0.080 (0.15)	-0.214 (0.43)	-0.397 (0.92)	0.431 (0.93)	2.352*** (3.07)
High-Low	5.298*** (4.44)	2.250** (2.20)	1.256 (1.20)	1.807* (1.82)	1.063 (1.43)	2.868*** (3.21)	

Table 3. The effect of R^2 on Characteristic Selectivity and Characteristic Timing

Estimation results of model (1). The dependent variables are monthly measures of two fund performance measures proposed by Daniel, Grinblatt, Titman, and Wermers (1997): *CS*, Characteristic Selectivity, and *CT*, Characteristic Timing. $R^2_{j,t-1}$ is estimated from the Fama-French-Carhart factor regression model using monthly returns over 24 months before the month for which *CS* and *CT* are measured. The logistic transformation of $R^2_{j,t-1}$ is $TR^2 = log[(\sqrt{R^2+c})/(1- \sqrt{R^2+c})]$, c = 0.5/n, n is the sample size of the estimation period. The variables are described in Table 1 and they include nine style dummy variables. The cross-section estimation is by the Fama-MacBeth method over the test periods, 204 months for *CS* (1990-2006) and 156 months for *CT* (1994-2006). Presented are the means of the coefficients and their *t*-statistics (in parentheses) and the weighted means and *t*-statistics of the coefficients, with the weight being inversely proportional to the standard error of the coefficient. Data for *CS* and *CT* are obtained from Russ Wermers.

Explanatory variables,	Dependent variables			
lagged	***CS***	***CT***	***CS***	***CT***
TR^2	-1.374 (2.95)	-0.168 (0.67)		
Weighted mean	-0.874 (2.64)	-0.043 (0.33)		
R^2			-9.679 (2.87)	-1.246 (0.77)
Weighted mean			-6.549 (2.72)	-0.387 (0.44)
Expenses	0.007 (0.02)	-0.188 (1.33)	0.019 (0.06)	-0.185 (1.31)
log(TNA)	-0.044 (0.12)	0.275 (1.85)	-0.053 (0.15)	0.278 (1.85)
$[log(TNA)]^2$	0.010 (0.37)	-0.017 (1.50)	0.010 (0.36)	-0.017 (1.50)
Turnover	0.002 (0.68)	0.002 (1.31)	0.002 (0.67)	0.002 (1.31)
log(Fund Age)	0.150 (1.05)	-0.068 (0.90)	0.149 (1.04)	-0.069 (0.91)
log(Manager Tenure)	-0.036 (0.39)	0.118 (1.06)	-0.036 (0.38)	0.114 (1.01)
R-sqr	0.09	0.08	0.10	0.08

Table 4. The effect of R^2 on stock fund *alpha* – cross-section regressions

Estimation results of Model (3) with the dependent variable being $alpha_{j,t}$, using monthly returns. $R^2_{j,t-1}$ and $alpha_{j,t-1}$ (the regression intercept) are obtained from regressions of fund-*j* monthly return (in excess of the one-month T-bill rate) on the returns of the Fama-French-Carhart factor model. The estimation period is of 24 month preceding the test period of one month. The test-month $alpha_{j,t}$ is the difference between the fund's excess return and the predicted fund return, obtained by multiplying the factor loadings (β) from the preceding estimation period by the factor returns in the test month. The estimation and test periods are rolling one month at a time. Fund returns, obtained from CRSP, are net of expenses. The logistic transformation of R^2 is $TR^2 = log[(\sqrt{R^2}+c)/(1- \sqrt{R^2}+c)]$, c = 0.5/n, n is the sample size of the estimation period. The control variables are explained in Table 1 and they also include nine style dummy variables. The cross-section estimation is done by the Fama-MacBeth method over 252 months, 1/1990-12/2010. We present the means of the coefficients with their *t*-statistics in parentheses. "Med" is the median coefficient. "Neg" is the proportion of negative coefficients. $^+$ indicates that this proportion is significantly different from ½ (the chance proportion) at the 0.05 level. The table includes the weighted means and *t*-statistics of the coefficients of TR^2 and R^2; the weights are inversely proportional to the standard errors of the coefficients.

Panel A: The effect of $R^2_{j,t-1}$ on $alpha_{j,t}$

Explanatory variables, lagged	Dependent variable: $alpha_{j,t}$	
TR^2	-1.045 (2.94)	
	Med: -0.711	
	Neg: 144/252$^+$	
Weighted mean	-0.930 (3.69)	
R^2		-8.212 (2.85)
		Med: -6.824
		Neg: 142/252$^+$
Weighted mean		-6.780 (3.60)
Expenses	-0.823 (3.72)	-0.803 (3.64)
log(TNA)	-0.304 (1.14)	-0.308 (1.16)
$[log(TNA)]^2$	0.015 (0.64)	0.015 (0.64)
Turnover	0.001 (0.42)	0.001 (0.41)
log(Fund Age)	0.120 (0.92)	0.127 (0.99)
log(Manager Tenure)	-0.033 (0.34)	-0.037 (0.38)
Alpha	0.309 (6.27)	0.309 (6.28)
R-sqr	0.13	0.13

Panel B: The prediction of fund $alpha_{j,t+k}$ by $R^2_{j,t-1}$ up to six months ahead

Estimation results of Model (3). The table shows the coefficients of $TR^2_{j,t-1}$ and of $R^2_{j,t-1}$ in predicting the fund $alpha_{j,t+k}$ in months $t+1$ to $t+5$. The values of R^2 are estimated over 24 months as of month $t-1$. The model includes all the explanatory variables that appear in Panel A, with values as of month $t-1$.

Explanatory Variables, lagged	*t+1*	*t+2*	*t+3*	*t+4*	*t+5*
TR^2	-1.063 (2.87)	-1.118 (2.73)	-1.237 (2.92)	-1.311 (3.08)	-1.187 (2.79)
	Med: -0.844	Med: -0.783	Med: -1.105	Med: -1.250	Med: -1.011
	Neg: 144/251$^+$	Neg: 143/250$^+$	Neg: 147/249$^+$	Neg: 147/248$^+$	Neg: 139/247$^+$
Weighted mean	-0.863 (3.32)	-0.902 (3.24)	-0.897 (3.16)	-0.942 (3.31)	-0.850 (2.99)
R^2	-8.024 (2.75)	-8.523 (2.69)	-9.347 (2.89)	-9.868 (3.07)	-8.844 (2.77)
	Med: -6.800	Med: -8.157	Med: -8.228	Med: -8.398	Med: -7.597
	Neg: 141/251$^+$	Neg: 147/250$^+$	Neg: 145/249$^+$	Neg: 152/248$^+$	Neg: 148/247$^+$
Weighted mean	-6.550 (3.38)	-6.910 (3.31)	-6.764 (3.20)	-7.155 (3.39)	-6.380 (3.03)

Table 5. The effects of R^2 and *Active Share* on fund *alpha*

Estimates of model (3), adding Cremers and Petajisto's (2009) Active Share (*AS*), the sum of absolute deviations of a fund's stock holdings (weights) from those of its benchmark portfolio. We use the last available *AS* before the one-month test period. TR^2 and *TAS* are the logistic transformations of R^2 and *AS*, respectively. Both variables are censored, 0.5% in each tail. Details of the estimation procedure are provided in the legend of Table 4. The cross-section estimation is by the Fama-MacBeth method. To save space, the coefficients of the control variables are not shown. There are 204 observations from 01/1990 to 12/2006. In parentheses there are the *t*-statistics.

Explanatory variables, lagged	Dependent variable: $alpha_{j,t}$			
TR^2 *Weighted mean*	-1.026 (2.15) -1.058 (3.26)	-0.939 (2.05) -0.911 (2.92)		
TAS *Weighted mean*	0.463 (1.64) 0.168 (0.80)	0.302 (1.09) -0.035 (0.17)		
R^2 *Weighted mean*			-8.356 (2.41) -8.126 (3.42)	-7.656 (2.29) -6.778 (2.94)
AS *Weighted mean*			2.671 (1.72) 0.953 (0.80)	1.659 (1.10) -0.103 (0.09)
Fund characteristics (see Table 4)	Yes	Yes	Yes	Yes
Alpha	No	Yes	No	Yes

Table 6. Determinants of R^2

The dependent variable is $TR^2_{j,t}$, the logistic transformation of $R^2_{j,t}$ which is estimated from non-overlapping 24-month regressions of monthly fund returns (in excess of the T-bill rate) on FFC factors returns for the years 1991-2010. There are 10 such periods. All explanatory variables are as of the end of the year before the beginning of the 24-month estimation period. The variables are as in Table 2. The estimation is by panel regression. The regressions also include time dummy variables and the errors are clustered by time periods and funds.

Explanatory variables, lagged	Dependent variable: $TR^2_{j,t}$
Expenses	-0.204 (10.12)
log(TNA)	0.089 (3.70)
[log(TNA)]²	-0.004 (1.99)
Turnover	-0.0002 (0.99)
log(Fund Age)	-0.011 (1.02)
log(Manager Tenure)	-0.072 (4.54)
<u>*Style dummy variables*</u>	
Aggressive Growth	-
Equity Income	0.076 (1.66)
Growth	0.126 (3.71)
Long term growth	0.076 (2.29)
Growth and Income	0.205 (5.59)
Mid-Cap	0.030 (0.71)
Micro-Cap	0.038 (0.54)
Small Cap	0.144 (2.29)
Maximum Capital Gains	0.076 (1.58)
R-sqr	0.39

Table 7. The effect of R^2 on Bond fund *alpha*

Estimation results of model (3) for bond mutual funds for the years 2001-2010. There are 20 semi-annual test periods during which we estimate the fund's $alpha_{j,t-1}$ (the regression intercept) from a multi-factor model, each preceded by a half-year estimation period from which we obtain estimates of $R^2_{j,t-1}$ and $alpha_{j,t-1}$. The regressions employ daily factors returns, current and two lags. Included are funds that have at least 35% of their holdings in corporate bonds. Excluded are Treasury, government or municipal bond funds. One benchmark model, following Bessembinder et al. (2008), includes the three Fama-French (1993) factors and two bond-spread factors: *DEF*, the difference between the return on BAA-rated bonds and AAA-rated bonds and *TERM*, the difference between the return on Treasury 30-year bonds and the 3-month Treasury bill rate. The second model, following Elton et al. (1995), includes four factors: The excess returns on the stock market index (CRSP value-weighted index) and on the aggregate bond market index (Barclays US Aggregate Bond index from Datastream), *DEF* and *OPTION*, the return spread between Barclays GNMA index and the Barclays Government Intermediate index from Datastream. The cross-section estimation is by the Fama-MacBeth method and includes 9 style dummy variables. $^+$ indicates that the proportion of negative coefficients is different from ½ at the 0.05 level of significance and * indicates significance at the 0.06 level.

Explanatory variables, lagged	Bessembinder et al.'s (2008) model		Elton et al.'s (1995) model	
TR^2 *Weighted mean*	-0.921 (4.18) Med: -1.028 Neg: 16/20$^+$ -0.856 (4.87)		-1.048 (2.58) Med: -0.882 Neg: 15/20$^+$ -0.818 (4.26)	
R^2 *Weighted mean*		-3.881 (4.39) Med: -3.926 Neg: 16/20$^+$ -3.547 (4.75)		-4.147 (2.65) Med: -2.500 Neg: 14/20* -3.047 (3.99)
Expenses	-0.865 (0.92)	-0.794 (.84)	-1.372 (1.47)	-1.325 (1.39)
log(TNA)	-0.040 (0.04)	-0.081 (0.09)	-0.258 (0.27)	-0.294 (0.31)
$[log(TNA)]^2$	0.0003 (0.00)	0.004 (0.06)	0.006 (0.08)	0.009 (0.13)
Turnover	0.003 (2.05)	0.003 (2.02)	0.001 (1.15)	0.001 (1.24)
log(Fund Age)	-0.225 (1.06)	-0.239 (1.14)	0.033 (0.12)	0.023 (0.08)
log(Manager Tenure)	0.061 (0.24)	0.074 (0.28)	0.088 (0.35)	0.092 (0.37)
alpha	0.224 (4.24)	0.224 (4.22)	0.284 (4.68)	0.285 (4.67)
R-sqr	0.56	0.56	0.55	0.55

Appendix:

Table A1. The effects of R^2, *Return Gap* and *Industry Concentration Index* on fund *alpha*
(Kacperczyk, Sialm and Zheng, 2005, 2008)
The dependent variable is *alpha*, using the FFC benchmark model. See Table 4 for details on the estimation procedure of *alpha* and R^2 and on the model's coefficients. *Industry Concentration Index* (*ICI*) (Kacperczyk et al., 2005) is the sum of the squared deviations of the fund's weights in various industries from the weights of these industries in the market portfolio. *ICI* value is of the month which precedes the test month. *Return Gap* (*RGap*) (Kacperczyk et al., 2008) is the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings; we use the average value of the 12 months preceding the test month. Data on *ICI* and *RGap* are obtained from Marcin Kacperczyk. TR^2 and *TICI* are the logistic transformations of R^2 and *ICI*, respectively. The sample period is 1990-2009. The estimation is by the Fama-MacBeth method. We present the means of the coefficients with their *t*-statistics in parentheses. To save space, the coefficients of the control variables are not shown. The model is estimated with and without lagged fund *alpha* estimated over the 24 estimation period that precede the test period.

Explanatory variables, lagged	Estimation model			
	Using *ICI*		Using *RGAP*	
TR^2 *Weighted mean*	-1.084 (2.29) -1.332 (3.90)	-0.910 (1.99) -1.031 (3.15)	-1.375 (3.53) -1.204 (4.35)	-1.139 (2.98) -0.903 (3.38)
TICI *Weighted mean*	0.463 (1.16) -0.150 (0.50)	0.257 (0.69) -0.204 (0.71)		
RGap *Weighted mean*			0.074 (2.71) 0.098 (4.72)	0.006 (0.23) 0.030 (1.50)
Fund characteristics (see Table 5)	Yes	Yes	Yes	Yes
Alpha	No	Yes	No	Yes

Table A2. The effect of R^2 on portfolio *alpha* using the Fama-French 100 portfolios, sorted on size and on book-to-market ratio, and 48 industry portfolios

The dependent variable is $alpha_{j,t}$, and the explanatory variable is $TR^2_{j,t-1}$, the logistic transformation of R^2, estimated as in Table 4, Panel A. There are two sets of portfolios: Fama-French's 100 (10x10) portfolios sorted on size and book-to-market ratio, and 48 industry portfolios. The estimations use monthly portfolio excess returns and employ the FFC benchmark factor model. The regression includes dummy variables that mimic style. *D-micro cap* equals 1 for the two smallest-size decile portfolios and zero otherwise, *D-small cap* equals 1 for decile portfolios 3 and 4 and zero otherwise, *D-growth* equals 1 for the lowest 3 book/market decile portfolios and zero otherwise, and *D-value* equals 1 for the highest 3 book/market decile portfolios and zero otherwise. The estimation includes 252 months, 1/1990 to 12/2010 and is done by the Fama-MacBeth method. Presented are the means of the coefficients and their *t*-statistics in parentheses.

Explanatory variables, lagged	Dependent variable: $alpha_{j,t}$			
	100 Size/BM Portfolios		48 Industry Portfolios	
TR^2 *Weighted mean*	0.237 (0.28) 0.080 (0.11)		0.193 (0.16) 0.487 (0.47)	
R^2 *Weighted mean*		1.161 (0.25) 2.782 (0.77)		1.387 (0.27) 1.567 (0.37)
Alpha	0.174 (2.93)	0.173 (2.93)	0.133 (1.63)	0.135 (1.66)
D-micro cap	-0.035 (0.02)	-0.017 (0.01)		
D-small cap	-1.515 (2.05)	-1.527 (2.03)		
D-growth (low book/mkt)	-1.222 (1.62)	-1.241 (1.62)		
D-value (high book/mkt)	-0.998 (1.34)	-1.059 (1.44)		
R-sqr	0.16	0.17	0.11	0.12

Table A3. **The time-series factors effect on the coefficient of TR^2**

A time series regression of the monthly Fama-MacBeth coefficient γ_t from the cross-section regressions of $alpha_{j,t}$ on $TR^2_{j,t}$, whose results are presented in Table 4, on the FFC factor returns. The time period is 1990-2010. The *t*-statistics (in parentheses) are calculated using robust standard errors (White (1980)).

Factors	Dependent variable: γ_t	
Const.	-0.764 (2.07)	-0.868 (2.52)
RM-Rf	-37.843 (3.94)	-34.254 (3.47)
SMB	-5.356 (0.39)	
HML	-20.244 (1.35)	
UMD	-2.529 (0.20)	
Rsqr	0.09	0.08