Mutual Fund's R^2 as Predictor of Performance

Yakov Amihud
Ira Leon Rennert Professor of Finance, Stern School of Business, New York University

Ruslan Goyenko
Desautels Faculty of Management, McGill University

We propose that fund performance can be predicted by its R^2, obtained from a regression of its returns on a multifactor 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. (*JEL* G20, G11, G20, G23)

Recent studies show that fund performance is positively affected by active management, measured by the deviation of fund 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 difficult 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 multifactor 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 $1-R^2$, the proportion of the fund's variance that is due to idiosyncratic risk or multifactor

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tracking error variance. 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 multifactor 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 significantly 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 a significant *alpha* of 3.804% or higher in the subsequent period, 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), which 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 multifactor 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. Brands, Brown, and Gallagher (2006), Kacperczyk, Sialm, and Zheng (2005), Cremers and Petajisto (2009, henceforth C-P), and Cremers et al. (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 et al. (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 stock holdings are related to company-specific information that 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 a 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). As a benchmark we also employ the model of Cremers, Petajisto, and Zitzewitz (2010), denoted CPZC, which includes the excess return on the S&P 500 index and the returns on the Russell 2000 index minus the return on the S&P 500 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 either $alpha_j$, the risk-adjusted excess fund return based on either the FFC or the CPZC factor model, or 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_j^2, 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 variance of the fund tracking error (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&P 500-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 variance 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.

[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; Sun, Wang, and Zheng 2012). However, hedge fund returns suffer from reporting biases (see Agarwal, Fos, and Jiang 2010).

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 Center for Research in Security Prices (CRSP) Survivor-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 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: (1) aggressive growth, (2) equity income, (3) growth, (4) long-term growth, (5) growth and income, (6) mid-cap, (7) micro-cap funds, (8) small cap, and (9) 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/or “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 because of reporting conventions. Addressing Evans’s (2010) comment on 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 names missing in CRSP.

We set an estimation period of twenty-four months followed by a test period of one month (more details below).[3] In the estimation period we regress monthly

[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.

[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

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 twenty-four-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 twelve-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 with a sample of 237,290 observations for 2,460 funds.

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 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 a 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 $alpha_{t-1}$. We sort by $alpha_{t-1}$ 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 twenty-four months preceding month t. This procedure produces twenty-five (5×5) portfolios with an equal number of funds in each.[7] We require funds to have a defined style and a name

cannot persist even if it is a result of skill because it induces an inflow of funds that makes the fund grow in size and causes 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, Santini, and Aber (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 an outlier-type strategy or estimation error. Our results are similar if we winsorize the data instead.

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 twenty-five.

Table 1
Summary statistics on actively managed equity mutual 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

	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(*manager tenure*)	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*

(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 twenty-four 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 1,200 to annualize it.) The fund characteristics are as of the end of each twenty-four-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 twelve-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 B) The contemporaneous correlations for the control variables are estimated for the sample of monthly fund returns. * denotes significance at the 5% level.

in the CRSP database, 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 include 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-oneyear period (252 months) 1990–2010. We present for each portfolio the regression *alpha* (the regression intercept) and its t-statistic, using robust standard errors (following White 1980).

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 $alpha_{t-1}$,

[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.

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

Panel A: Results using *net* returns

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

Panel B: Results using *gross* returns

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

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 twenty-four-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). ***, **, and * denote significance at the 1%, 5%, or 10% level.

that is, 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 the $alpha_t$ 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 et al. 1997)

Daniel et al. (1997) propose two measures of fund performance: (1) "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, and (2) "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:

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

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):

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

where $c = 0.5/n$, and n is 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 twenty-four months preceding the test month and we employ the same sample selection criteria and data requirements that are 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 et al. (2004). For the $CS_{j,t}$ ($CT_{j,t}$) regressions, we estimate the 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 in which $CS_{j,t}$ 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 in which $CT_{j,t}$ is the dependent variable.

Table 3, which presents the estimation results of Model (1), shows that R^2 significantly predicts *CS* with a 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

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

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

Table 3
The effect of R^2 on characteristic selectivity and characteristic timing

Explanatory variables, lagged	Dependent variables			
	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^2	0.09	0.08	0.10	0.08

Estimation results of Model (1). The dependent variables are monthly measures of two fund performance measures proposed by Daniel et al. (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 twenty-four months before the month for which *CS* and *CT* are measured. The logistic transformation of $R^2_{j,t-1}$ is $TR^2 = log[(\sqrt{R^2}+c)/(1-\sqrt{R^2}+c)]$, $c=0.5/n$, and 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). The means of the coefficients and their t-statistics (in parentheses) and the weighted means and t-statistics of the coefficients are presented, with the weight being inversely proportional to the standard error of the coefficient. Data for *CS* and *CT* are obtained from Russ Wermers.

γ_t, that is, 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 $TR^2_{j,t-1}$, 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. Whereas $R^2_{j,t-1}$ predicts fund performance associated with selectivity, it does not predict fund performance based on timing, measured by CT_{jt} 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*, whereas other predictive variables—C-P's Active Share and Kacperczyk, Sialm, and Zheng's (2005, 2008). Industry Concentration Index and Return Gap (both discussed below)—have a 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 the risk-adjusted monthly return $alpha_{j,t}$. 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 twenty-four months (see, e.g., Cremers et al. 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:

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

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 $alpha_{j,t-1}$).

We hypothesize 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 twenty-one-year sample period of 1990–2010. The sample is the one used in Table 1.

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

[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.

Table 4
The effect of R^2 on stock fund *alpha*: Cross-section regressions

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^2	0.13	0.13

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

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)

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 twenty-four months as of month $t-1$. The model includes all the explanatory variables that appear in Panel A, with values as of month $t-1$.

proportion of negative coefficients is 144/252, significantly different from one-half which is the chance result ($p < 0.05$), 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 one-half ($p<0.01$). 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 one-half ($p<0.01$). 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 one-half, 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%.

Among the control variables, the coefficient of $Expenses_{j,t-1}$ is negative and significant and that of $alpha_{j,t-1}$ is positive and significant. The coefficients of the other fund characteristics are statistically insignificant, including that of fund size (*TNA*). The latter result is unlike that of Chen et al. (2004) and it is consistent with the result in Elton, Gruber, and Blake (2011).

The predictive power of R^2 holds for at least six 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 a 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 use *daily* returns data to replicate our analysis. We set sequences of forty-two non-overlapping half-year test periods over the twenty-one 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 fifty 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 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 Survivor-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 semiannual 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 forty-two half-year test periods, where the values of the control variables are as of the end of the estimation period that 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 one-half ($p<0.01$). 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 twenty-one times the (absolute) mean of γ_t and 4.4 standard deviations greater

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12 We replicate this analysis with the test period $alpha_{j,t}$ being, as in Table 4, 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 then averaged over the one-half year test period. By this procedure, we obtain that the mean γ_t is more negative and significant than that reported here.

13 Cremers, Petajisto, and Zitzewitz (2010, p. 36) contend, however, that the average staleness in fund return is likely to be close to that in benchmark index return.

14 This may cause a problem of survivorship bias, which is expected to be minor.

than the mean. We recalculate 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 forty 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 forty semiannual 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 forty-two semiannual 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 one-half ($p<0.01$). (The detailed results are available on the *RFS* Web site.)

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 et al. (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, whereas 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 twenty-four-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&P 500 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&P 500 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, although it is in fact a passive indexer. However, its R^2 will be close to one, 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 multifactor 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, whereas 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 although doing passive multi-index investing. Measuring active fund management by R^2 enables to exclude strategies that can be homemade by investors who invest passively in indexes. Notably, if a fund loads on a risk factor that is not among the identified benchmark factors, both *AS* and R^2 will predict abnormal performance which is in fact compensation for the unidentified risk factor.[15]

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.

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, $TAS = log[(AS+c)/(1-AS+c)]$,

15 This problem applies to other measures that predict fund performance, for example, the Industry concentration index proposed by Kacperczyk, Sialm, and Zheng (2005) and discussed below.

Table 5
The effects of R^2 and *active share* on fund *alpha*

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

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. There are the t-statistics in parentheses.

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 although R^2 and *AS* are related measures of active management, 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 an 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 $t=2.22$. 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 because both variables capture the effect of selectivity or active management on fund performance.

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 a 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* Web site).

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, Sialm, and Zheng (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, Sialm, and Zheng (2008) propose a predictor of fund performance that 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 Mechanical?

The negative relation between $alpha_{j,t}$ and $R^2_{j,t-1}$ could be spurious rather than 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. Because $R^2 = \hat{b}\text{'}F\text{'}r(r\text{'}r)^{-1}$, 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 four tests of robustness. In the first test we regress the monthly estimate of γ_t, obtained from Model (3) (and whose statistics are presented in Table 4, Panel A), on the monthly FFC factor returns and a constant. We test whether the constant is negative and significant after accounting for the effects of the factor returns on the estimated γ_t. The results are presented in the Appendix Table A2. The factor coefficients in this regression are negative (only the coefficient of *RM-Rf* is significant). Importantly, the intercept is 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 $t = 2.52$. 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 second robustness test we modify the procedure employed in Table 2, where we divide the funds into twenty-five portfolios, sorted by their $alpha_{j,t-1}$ and $R^2_{j,t-1}$. Now, instead of regressing the portfolio average of the fund monthly excess return on the FFC factors returns, we use as dependent variable the portfolio average of the fund monthly risk-adjusted return $alpha_{j,t}$ which is used as dependent variable in Model (3). If the negative relation between $R^2_{j,t-1}$ and $alpha_{j,t}$ is mechanical and related entirely to the factor values, the *alpha* (intercept) from this regression should be zero. However, this is not the case. The results are qualitatively similar to those presented in Table 2, Panel A. The portfolio with the lowest $R^2_{j,t-1}$ and highest $alpha_{j,t-1}$ has *alpha*= 3.116% (t=3.49) compared with *alpha*=3.804% (t=3.87) in Table 2, Panel A. For the margin portfolios of low-minus-high $R^2_{j,t-1}$ we obtain that for the highest and second-highest $alpha_{j,t-1}$ quintiles, this strategy yields *alpha* of 3.637% (t=4.42) and 2.013% (t=3.08), respectively, compared with *alpha* of 4.990% (t=4.02) and 2.710% (t=3.24) in Table 2, Panel A. The *alpha* of the overall low-minus-high $R^2_{j,t-1}$ portfolio is 1.212% with t=2.54. This shows again that the funds' $alpha_{j,t}$ is significantly higher for funds with low $R^2_{j,t-1}$ after accounting for the effects of the FFC factors on this relation.

The third test replicates the procedure employed in estimating Table 4 on Fama and French's 100 (10 × 10) portfolios sorted by size and by book-to-market ratio and on 48 industry portfolios. As in Table 4, Panel A, we do cross-section Fama-MacBeth regressions of the test month's $alpha_{j,t}$ on $TR^2_{j,t-1}$ and on $alpha_{j,t-1}$. The model includes dummy variables to emulate styles[16] and a constant. The results are presented in the Appendix Table A3. 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 below 1.0). In a further test we add to the model eight dummy variables that account for the interaction between size and Book/Market rankings[17] and estimate the monthly cross-section regression of the portfolios' $alpha_{j,t}$ on $TR^2_{j,t-1}$, $alpha_{j,t-1}$ and the dummy variables (some coefficients of the dummy variables are significantly different from zero). We obtain that the mean coefficient of $TR^2_{j,t-1}$ is −0.86 with t=0.92. Regressing this monthly coefficient on the FFC factors returns and a constant as we do for active funds in the first robustness test, we obtain[18] that the intercept here is *positive*, 0.50 with t=0.57, whereas the respective intercept for the actively managed funds is negative and significant, as reported in Table A2.

In the fourth robustness test we use the Fama and French's 100 portfolios to replicate the procedure in the second robustness test. We divide these portfolios into twenty-five (5x5) groups based on their lagged $R^2_{j,t-1}$ and $alpha_{j,t-1}$ and then regress the average monthly $alpha_{j,t}$ of each group on the FFC returns. Unlike the results for actively managed funds in the second robustness test, here the estimated intercepts are insignificantly different from zero. The group with

[16] The dummy variables are: *D-micro cap*=1 for the two smallest-size decile portfolios, *D-small cap*=1 for decile portfolios 3 and 4, *D-growth*=1 for the lowest 3 book/market decile portfolios, and *D-value*=1 for the highest 3 book/market decile portfolios. The default value of these dummy variables is zero.

[17] Noting that portfolios are ordered first by size (portfolios 1-10 are the smallest size decile) and then by Book/Market, we use the following dummy variables. D1=1 for portfolios 1-5; D2=1 for portfolios 6-10; D3=1 for portfolios 91-95; D4=1 for portfolios 96-100; D5=1 for portfolios 1, 11, 21, 31, 41; D6=1 for portfolios 51, 61, 71, 81, 91; D7=1 for portfolios 10, 20, 30, 40, 50; D8=1 for portfolios 60, 70, 80, 90, 100. The default value of these dummy variables is zero.

[18] The coefficients of all factors are negative; those of *RM-Rf* and *HML* are significant.

the lowest $R^2_{j,t-1}$ and highest $alpha_{j,t-1}$ has *alpha* (intercept) of 0.05 (t=0.03) compared with *alpha*=3.116 (t=3.49) reported in the second robustness test which uses active-fund returns. For the marginal group of low-minus-high $R^2_{j,t-1}$ portfolios we obtain that for the highest and second-highest $alpha_{j,t-1}$ quintiles, this strategy yields *alpha* of 1.394% (t=0.69) and −0.338 (t=0.13), respectively, compared with *alpha* of 3.637% (t=4.42) and 2.013 (t=3.08) for the analogous portfolios of active funds in the second robustness test. These results suggest that the negative and significant relation between $R^2_{j,t-1}$ and $alpha_{j,t}$ for actively managed funds is not a mechanically-obtained result.

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 twenty-four months, we use here ten nonoverlapping periods of twenty-four months from 1991 to 2010. The fund characteristics are as of the end of the year before the beginning of the twenty-four-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.

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, suggesting 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 that have better performance because it is harder for them to replicate the strategies of such funds on their own. 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

Table 6
Determinants of R^2

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)
Style dummy variables	
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^2	0.39

The dependent variable is $TR^2_{j,t}$, the logistic transformation of $R^2_{j,t}$ which is estimated from nonoverlapping twenty-four-month regressions of monthly fund returns (in excess of the T-bill rate) on FFC factors returns for the years 1991–2010. There are ten such periods. All explanatory variables are as of the end of the year before the beginning of the twenty-four-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.

by increasing their fund size have an incentive to "deviate from the pack" and employ idiosyncratic investment strategies (see Krasny 2010). 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 that 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, whereas growth funds (*Growth and income*, *Growth and long-term growth*) as well as the 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, that is, 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.[19] This is consistent with our results in Section 4 and Table 3 that R^2 does not predict the fund's performance because of timing.

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 us 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 thirty-year bonds and the three-month Treasury bill rate. The bond data are the Lehman\Barclays series, obtained from Datastream. The second model, following Elton, Gruber, and Blake (1995), includes the stock market excess returns (using CRSP value-weighted market return), the aggregate bond market returns (using Barclays U.S. 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 for which at least 35% of their net asset value have been invested in corporate bonds. This accommodates "balanced

19 Interestingly, Elton, Gruber, and Blake (2009) find that application of market timing worsens rather than improves fund performance.

funds,"[20] 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 half-year test period t and for each fund j we estimate $alpha_{j,t}$, the intercept from a regression of the fund excess return on the factors returns,[21] 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 return of the current day and the two days lagged returns, 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 twenty 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 fifty 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 this sample, the average proportion invested in corporate bonds is 69.5%, and the 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) $R^2_{j,t-1}$ of the funds in the sample that uses the model of Bessembinder et al. (2008) is 0.53 (0.50), ranging between 0.165 and 0.985. For the model of Elton, Gruber, and Blake (1995), the mean (median) $R^2_{j,t-1}$ 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 nine style dummy variables.[22] The results in 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 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 one-half ($p < 0.01$). Employing the benchmark

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20 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%."

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

22 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 multisector), and flexible portfolio.

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

Explanatory variables, lagged	Bessembinder et al.'s (2008) model		Elton, Gruber, and Blake (1995) model	
TR^2	−0.921 (4.18) Med: −1.028 Neg: 16/20$^+$		−1.048 (2.58) Med: −0.882 Neg: 15/20$^+$	
Weighted mean	−0.856 (4.87)		−0.818 (4.26)	
R^2		−3.881 (4.39) Med: −3.926 Neg: 16/20$^+$		−4.147 (2.65) Med: −2.500 Neg: 14/20*
Weighted mean		−3.547 (4.75)		−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^2	0.56	0.56	0.55	0.55

Estimation results of Model (3) for bond mutual funds for the years 2001–2010. There are twenty semiannual test periods during which we estimate the dependent variable—the fund's $alpha_{j,t}$ (the regression intercept)—from a multifactor regression model. Each test 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 thirty-year bonds and the three-month Treasury bill rate. The second model, following Elton, Gruber, and Blake (1995), includes four factors: the excess returns on the stock market index (CRSP value-weighted index) and on the aggregate bond market index (Barclays U.S. 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 nine style dummy variables. $^+$ indicates that the proportion of negative coefficients is different from one-half at the 0.05 level of significance, and * indicates significance at the 0.06 level.

model of Elton, Gruber, and Blake (1995), we obtain that the mean γ_t is -1.048 with $t=2.58$, and the weighted mean coefficient is -0.818 with $t=4.26$.

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 one-half ($p<0.01$). For Elton, Gruber, and Blake's (1995) benchmark model, the mean γ_t is -4.147 ($t=2.65$), and the weighted mean is -3.047 ($t=3.99$). The proportion of negative coefficients is $14/20$, enabling to reject the null that the proportion is one-half at $p<0.06$. Notably, the coefficients of $TR^2_{j,t-1}$ and $R^2_{j,t-1}$ for bond funds are lower than they are for stock funds.

As in the estimates of Table 4 for stocks, $alpha_{j,t-1}$ is a significant predictor of fund performance. The coefficient of $Expenses_{j,t-1}$, although 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 multifactor 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 twenty-five (5×5) 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 that 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.

Appendix

Table A1
The effects of R^2, *Return Gap*, and *Industry Concentration Index* on fund *alpha* (Kacperczyk, Sialm, and Zheng 2005, 2008)

Explanatory variables, lagged	Dependent variable: $alpha_{j,t}$			
TR^2	−1.084 (2.29)	−0.910 (1.99)	−1.375 (3.53)	−1.139 (2.98)
Weighted mean	−1.332 (3.90)	−1.031 (3.15)	−1.204 (4.35)	−0.903 (3.38)
TICI	0.463 (1.16)	0.257 (0.69)		
Weighted mean	−0.150 (0.50)	−0.204 (0.71)		
RGap			0.074 (2.71)	0.006 (0.23)
Weighted mean			0.098 (4.72)	0.030 (1.50)
Fund characteristics (see Table 5)	Yes	Yes	Yes	Yes
Alpha	No	Yes	No	Yes

The dependent variable is $alpha_{j,t}$ 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, Sialm, and Zheng 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 preceding the test month. *Return Gap* (*RGap*) (Kacperczyk, Sialm, and Zheng 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 twelve 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 twenty-four month estimation period preceding the test period.

Table A2
The time-series factors effect on the coefficient of TR^2

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)	
R^2	0.09	0.08

A time-series regression of the monthly Fama-MacBeth coefficient γ_t from the cross-section regressions of $alpha_{j,t}$ on $TR^2_{j,t-1}$, whose results are presented in Table 4, Panel A, on the FFC factor returns. The time period is 1990–2010. The t-statistics (in parentheses) are calculated using robust standard errors (White 1980).

Table A3
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

Explanatory variables, lagged	Dependent variable: $alpha_{j,t}$			
	100 size/BM portfolios		48 industry portfolios	
TR^2	0.237 (0.28)		0.193 (0.16)	
Weighted mean	0.080 (0.11)		0.487 (0.47)	
R^2		1.161 (0.25)		1.387 (0.27)
Weighted mean		2.782 (0.77)		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^2	0.16	0.17	0.11	0.12

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 (10×10) 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 one for the two smallest-size decile portfolios and is zero otherwise; *D-small cap* equals one for decile portfolios 3 and 4 and is zero otherwise; *D-growth* equals one for the lowest three book/market decile portfolios and is zero otherwise; and *D-value* equals one for the highest three book/market decile portfolios and is zero otherwise. The estimation includes 252 months, 1/1990 to 12/2010, and is done by the Fama-MacBeth method. The means of the coefficients are presented, and their t-statistics are in parentheses.

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