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Endogenous benchmarks

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endogenous benchmarks

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Endogenous Benchmarks*

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*E. Kandel, D. Hunter, and R. Wermers dedicate this paper to the memory of Shmuel Kandel. Corresponding author email: rwormers@rhsmith.umd.edu. E. Kandel and S. Kandel gratefully acknowledge the support of the Israeli Science Foundation. E. Kandel would also like to thank Krueger Center for Finance Research at Hebrew University for financial support.

Endogenous Benchmarks

Abstract

This paper develops a new approach that controls for commonalities in actively managed investment fund returns when measuring their performance. It is well-known that many investment funds may systematically load on common priced factors omitted from popular models, exhibit similarities in their choices of specific stocks and industries, or vary their risk-loadings in a similar way over time. We propose a parsimonious model that uses the return on the group of mutual funds as a benchmark for each individual fund within that group. We demonstrate that this model substantially reduces the correlation between fund residuals from standard models used for equity and fixed-income funds, and improves the estimates of fund α 's and β 's from commonly used equity and fixed-income models.

I. Introduction and Motivation

The open-end mutual fund industry is the main venue through which retail investors invest in traded securities. The industry has been growing rapidly during the last few decades – in fact, the total number of equity funds in the U.S. now exceeds the number of stocks traded on the New York Stock Exchange.

A growing number of funds follow a passive strategy, linking their investments to a particular index. The majority, however, still claim that they can add value to investors by actively managing their portfolios. The basic question facing academics, regulators, and investors alike is whether the active fund managers deliver superior performance to investors, as they claim, or just solicit additional funds when they are lucky, and downplay their performance when they are not. Consequently, the literature on active fund management has been expanding rapidly. It attempts to answer the basic question: are we able to detect whether active management produces superior investment performance that persists over time?

The literature evolved from simple Sharpe ratio comparisons to Jensen's alpha using a single risk factor, to Fama and French (1993) three-factor model, to which Carhart (1997) added the momentum as the fourth factor. Subsequently, the literature tried to account for time-varying factor loadings using conditional β 's (e.g., using macroeconomic variables, as in Ferson and Schadt (1996), Ferson and Siegel (2003), and Avramov and Wermers (2006), or with Kalman filters, as in Mamaysky, Spiegel and Zhang (2003). This branch of literature uses exogenously-determined risk factors that are imposed by the researcher on all funds. Most research in this area is limited to US domestic equity funds, for which there exist accepted benchmarks. Extensive literature reviews can be found in Wermers (2000), and Carhart et al. (2000).¹

An ongoing problem with performance evaluation is the presence of similar strategies among funds, which produce correlated residuals from commonly used models and, therefore,

¹Another branch tries to attribute the performance to various types of decisions made by the manager: asset allocation, security selection, and high frequency market timing. Such analyses require data on fund holdings, which became available and widely used in the last decade. Examples are Daniel, Grinblatt, Titman, and Wermers (1997), Wermers (2000), and Kosowski et al (2006).

reduce the power of such models to identify skilled fund managers. Jones and Shanken (2005) and Cohen, Coval, and Pastor (2005) recognize this issue, and develop approaches to exploit commonalities in fund returns to improve performance evaluation. However, these papers require fund portfolio holdings data or knowledge about the commonalities that may not be available in practice.

In this paper, we propose a simple approach to accounting for the commonalities in fund strategies that only uses information on fund returns and the investment objective of the fund. Our approach is to form an additional “factor” from the return on the group of funds to which a given fund belongs, which we call the “endogenous benchmark,” since each fund manager chooses the group within which it intends to compete.² We note that it is much simpler to determine the reference group for a fund, e.g., funds that label themselves as “growth funds,” as opposed to determining commonalities in their complex strategies. As such, we postulate several reasons for using this variable as an additional factor. We must stress, that while we call it an additional factor for convenience, we do not imply that it is necessarily priced (this question is left for future research). In this paper, we use it only to improve the estimation of the parameters of interest.

First, let us take the point of view of the investor, who already made the asset allocation decision in terms of choosing the type of funds in which she would like to invest (e.g., Growth vs. Value), but needs help in choosing the best funds within the reference group. The least sophisticated investor has a fallback strategy of equally-weighting (or value-weighting) all funds in the group every period—this strategy is always feasible and is quite simple.³ To obtain a higher share of an investor’s portfolio, the fund manager must convince the investor that the fund can deliver superior performance, relative to this naive strategy of investing in the entire group. Superior performance is calculated, of course, by controlling for the risk of the fund relative to the same strategy. Consequently, we can use the group investment as an endogenously-determined benchmark for each fund that belongs to that group. We claim that, by choosing the strategy and advertising herself as managing a growth fund, the manager implicitly chooses the benchmark of growth funds, thus it is only natural to

²In principle, group classification can be based on self-proclaimed goals of the fund manager, or determined ex post from her actual investment strategy. We use the former method.

³We only consider no-load funds, thus the cost of rebalancing is low.

evaluate her performance using the portfolio of all growth funds during the same time period. In effect, using the entire reference group to benchmark the individual funds for risk has an alternative investment interpretation: it focuses on identifying the best strategies within that group.

Second, suppose we have identified several common risk factors for all funds that belong to a particular group, such as the market return, size, and book-to-market among a group of equity funds. It is likely that these funds expose their investors to additional priced factors that are not observed by the evaluator. If many funds in the group are exposed to these factors, then the group as a whole is exposed to them as well. We then show that the group return can be used to control for the average exposure to these factors, yielding a potentially better estimate of fund α .

Third, even if there are no hidden priced factors, it may well be that many fund managers in a group make similar bets. They may use similar models, have similar behavioral biases, or locate in the same geographical area. This would make the error terms in the individual funds returns (after controlling for the priced factors) correlated across funds in the same group. In such a case the group return also captures these commonalities. Then, as argued by Pastor and Stambaugh (2002), using group returns in the regression improves the estimation of α . In the limiting case, if all funds in a group use the same strategy, win or lose, then our approach will correctly indicate that there is no benefit of deviating from an investment in the entire group.

Finally, if the exposure of mutual funds to the known risk factors varies over time, and there is a common component in this variation across funds, then the group return captures this comovement as well. Following Ferson and Schadt (1996), it is easy to see that including group return as an explanatory variable also improves the estimation of α .

Apart from the above advantages, as well as its simplicity, our approach offers additional advantages: it allows evaluation of the performance of any fund, and is not limited to equities. For instance, while risk models are well-developed for most of the mutual funds that we consider (domestic equity, fixed-income), there are many asset classes where this is not so, such as hedge funds. Moreover, the benchmark is a tradeable asset, unlike most of the risk factors in the conventional models—one can easily invest equal amounts of one's

wealth in many mutual funds.

To demonstrate the effect of using an “endogenous benchmark,” we use data on U.S. mutual funds specializing in equities and in fixed income. We compare the performance of the standard models: the four-factor Carhart (1997) model for equity funds, and the six-factor Elton, Gruber, and Blake (1996) model for fixed-income funds with (1) the same models augmented by the endogenous (group) return as a “factor” and (2) models that use the endogenous return as the only factor.

We begin our analysis by documenting relatively large correlations between the four-factor residuals of equity funds applied to between group portfolios (e.g. Growth and Aggressive Growth). Similar results are found for residuals from the six-factor model for fixed-income funds. This suggests to us that there are significant unexplained commonalities across groups, which may represent omitted risk factors. It would be interesting to inquire whether this factor is priced, but we leave this question for future research.

Then we show that, after controlling for the four- or six-factor models for each fund within a group of equity or debt funds, respectively, the residuals remain highly correlated between individual funds within groups, up to 90% in some cases. Once we add the endogenous (group) factor to these specifications, the within-group correlations drop by between fifty to seventy percent, depending on the group.

Further, among several equity and fixed-income fund categories, we show that the endogenous factor alone accounts for over 90% of the explanatory power of the more complicated four-factor or six-factor models. The endogenous factor is significant for over half of the funds in the traditional equity categories, even after accounting for the standard factors. Perhaps even more noteworthy is that, for more exotic equity and fixed-income strategies, the endogenous factor (alone) outperforms the standard models in terms of its power to explain mutual fund returns. For instance, among Technology funds, the endogenous factor model explains 83% of return variation, while the four-factor model explains 81%.

While this is not the main point of the paper, we do test whether the augmented models estimate the ability of the managers to generate excess returns improves relative to the standard models. We have no clear prediction on that, as better estimation of Jensen’s α may actually imply lower predictability of future returns, if these superior abilities are non-

existent, and are correctly removed by our procedure. On the other hand, if they do exist, our procedure should improve the predictability. The results are inconclusive - both models seem to predict only in a very few categories and periods.

The paper is organized as follows. Section 2 presents the intuition behind the choice of the group return as an explanatory variable and presents simple econometric arguments for doing so. Section 3 describes the data, while section 4 presents the empirical methodology. Section 5 presents our results, while section 6 concludes.

II. Motivating Endogenous Benchmarks

Imagine a group of unsophisticated individuals interested in investing in actively managed mutual funds. They have already obtained expert advice on asset allocation, which means that they have already determined the amounts they would like to invest in each asset class. For simplicity, let us constraint ourselves to equities, and define broad asset classes and corresponding groups of funds: Aggressive Growth, Growth, and Growth and Income. They hire an advisor to suggest the allocation within each group of funds. It is clear to both parties that investors can always save the advisor’s fees by using a simple strategy of periodically rebalanced equally weighted portfolio of all the funds in the group. To justify the fee, the advisor must present an evaluation procedure that adds value over their default strategy.

The advisor can force exogenous benchmarks on these investors, but it is unlikely that these benchmarks represent their alternative investment. Instead, we propose treating the investors own default strategy as the benchmark. We refer to this as an “endogenous benchmark”, since it is determined by the investor’s choice of the asset group, and by the fund’s choice to belong to this group. This endogenous benchmark is the cornerstone of the proposed performance evaluation strategy. The investors are advised to modify their naive strategy and invest more in funds that generate positive excess risk-adjusted return, while less in those that generate a negative one.

The basic procedure we propose is to estimate Jensen’s α (intercept of the OLS), however instead of the four standard factors (see e.g. Carhart (1997), or Wermers (2000)), we use the excess return on the equally weighted portfolio of all the funds in the group. In computing

the periodic return of the default strategy we propose to use all the funds that were available for investment in that group at the beginning of each period. To make this alternative more realistic, we include only the no-load funds in our analyses.

The heterogeneity of the group in terms of investment strategies represents a problem. If all funds in the group invest roughly in the same assets, and vary only in the degree of exposure to the group benchmark, then the estimated Jensen’s α indeed captures the excess ability of the manager. However, if funds make significant investments in other assets, deviating from the group’s policy in several dimensions, then in addition to the manager’s ability the estimated Jensen’s α would capture the risk premia associated with these deviations. To control for these, one must use standard risk factors in addition to the group performance. In the context of the US domestic equity this would amount to using a five-factor model of mutual funds’ performance evaluation. This approach allows for easy comparison with the existing literature; and, as we show below, represents a solution to econometric problems associated with omitted risk factors and with time varying factor loadings.⁴

II.A. Econometric models

In this section we outline the econometric advantages of using the group return in addition to the traditional risk factors. But let us first define the main variables. We denote by $R_{i,t}$ the actual reported return of fund i during month t . This return is net of the management fee, as is customary in fund reporting. Let $m_{i,t}$ be the periodic percentage management fee that fund i charged at period t , and $r_{f,t}$ be the risk-free rate for the same period. Together we can use these variables to define the gross excess return of fund i at time t :

$$r_{i,t}^e \equiv R_{i,t} + m_{i,t} - r_f \tag{1}$$

We define by $r_{g,t}^e$ the average gross excess return of the group of funds to which fund i

⁴The shortcoming of this approach is that it deviates from our basic premise and again imposes external benchmarks on investors. This is especially problematic since many external benchmarks are not easily tradeable. An alternative is to extend the basic premise of our approach across asset classes and treat all group benchmarks as risk factors. This makes the comparison with the existing literature difficult, but is more consistent with our overall approach.

belongs:⁵

$$r_{g,t}^e \equiv \sum_{i=1}^I r_{i,t}^e \quad (2)$$

Next we present three simple specifications of this model to illustrate the potential advantages of adding the endogenous benchmark to the traditional estimation of Jensen's α .

II.A.1. Omitted factor model

Suppose that the excess gross return of a fund i at time t is spanned by two priced risk factors $f_{1,t}$ and $f_{2,t}$:

$$r_{i,t}^e = \alpha_i + \beta_{1,i}f_{1,t} + \beta_{2,i}f_{2,t} + \epsilon_{i,t}. \quad (3)$$

The problem is that an econometrician interested in estimating α_i can only observe the first factor realizations, thus can only run a regression on the observable factor:

$$r_{i,t}^e = \gamma_i + b_{1,i}f_{1,t} + \epsilon_{i,t}. \quad (4)$$

We know that in this case the coefficient estimate is biased:

$$E_t \widehat{b}_{1,i} = \beta_{1,i} + P_{1,2}\beta_{2,i},$$

where $P_{1,2}$ is the slope of the regression of $f_{2,t}$ on $f_{1,t}$. Then the expected intercept value is:

$$E_t \gamma_i = \alpha_i + \beta_{2,i}(E_t f_{2,t} - P_{1,2}E_t f_{1,t}) \quad (5)$$

Notice that the estimation error declines in the correlation between $f_{2,t}$ and $f_{1,t}$, assuming $E_t f_{1,t} > 0$. If the two factors are independent, then the error, $\beta_{2,i}E_t f_{2,t}$, is positive and could be quite significant in some periods. Moreover, if the $E_t f_{2,t}$ is large, small variations in the fund exposure to the unobserved risk factor, $\beta_{2,i}$, may change the estimated relative performance of the funds, which is usually of interest.

The proposed approach utilizes the fact that we observe returns of many funds. The average return in the fund population at time t contains the average loading of the funds in the group on the unobserved factor, thus can be used as a proxy. Formally,

$$r_{g,t}^e = \alpha_g + \beta_{1,g}f_{1,t} + \beta_{2,g}f_{2,t} + \epsilon_{g,t}. \quad (6)$$

⁵We proceed with identifying all the parameters/variables with subscript g with the group averages of the corresponding fund-specific parameters/variables.

where $\beta_{1,g}$ and $\beta_{2,g}$ are the average loadings on these factors in the group.

Let us first run the following regression:

$$r_{g,t}^e = \gamma_g + b_{1,g}f_{1,t} + \epsilon_{g,t}. \quad (7)$$

We know that in this case the coefficient estimate is biased:

$$E_t \widehat{b}_{1,g} = \beta_{1,g} + P_{1,2}\beta_{2,g},$$

where $P_{1,2}$ is the slope of the regression of $f_{2,t}$ on $f_{1,t}$.

We can then use the sum of the intercept and the residual to construct a new variable, which is the group return net of its exposure to the observed factor:

$$r_{g,t}^{net} \equiv r_{g,t}^e - b_{1,g}f_{1,t} = \alpha_g + \beta_{2,g}(f_{2,t} - P_{1,2}f_{1,t}) + \epsilon_{g,t}$$

Rewriting we obtain:

$$\beta_{2,i}f_{2,t} = -\lambda_i\alpha_g + \lambda_i r_{g,t}^{net} + \beta_{2,i}P_{1,2}f_{1,t} - \lambda_i\epsilon_{g,t}, \quad (8)$$

where

$$\lambda_i \equiv \frac{\beta_{2,i}}{\beta_{2,g}}.$$

Wooldridge (2002) (pp. 63-64) indicates that in case of an omitted variable, one can use a proxy to consistently estimate the relevant coefficients. There are two sufficient conditions for a “perfect” proxy: first, it has to be redundant, i.e. does not add explanatory power to a fully specified model; and second, that the omitted variable is uncorrelated with the observed explanatory variables, after the proxy is partitioned out of it. In the context of Equation (8) and the assumptions of this model the first condition is satisfied: group return does not add by itself to the explanatory power, when both factors are observable, i.e.:

$$E[r_{i,t}^e | f_{1,t}, f_{2,t}, r_{g,t}^{net}] = E[r_{i,t}^e | f_{1,t}, f_{2,t}]$$

Substituting (8) into (3) we obtain:

$$r_{i,t}^e = [\alpha_i - \lambda_i\alpha_g] + [\beta_{1,i} + P_{1,2}\beta_{2,i}]f_{1,t} + \lambda_i r_{g,t}^{net} + [\epsilon_{i,t} - \lambda_i\epsilon_{g,t}],$$

Unfortunately, the proxy, $r_{g,t}^{net}$ is correlated with $\epsilon_{g,t}$. This satisfies Wooldridge’s (2002) definition of an “imperfect” proxy. Wooldridge (2002, p.64) suggests that unless the proxy is highly correlated with the other regressors, it is usually worthwhile to introduce it, even though it also generates an inconsistent estimate, but it reduces the error. In our case, $r_{g,t}^{net}$ is uncorrelated with $f_{1,t}$ by construction, thus it makes sense to introduce it. We have performed numerous simulations estimating the bias in the estimate of α_i with and without the net group return. In all cases the bias without the group return was significantly larger. This leads us to believe that the introduction of $r_{g,t}^{net}$ improves the estimation of α_i .

II.A.2. Correlated Errors

An alternative scenario is when there are no unobserved priced factors, but the errors, $\epsilon_{i,t}$, are correlated across funds in the group due to some commonality in behavior of fund managers. Pastor and Stambaugh (2002) point out that under such scenario “...the estimates of the performance measurements can be improved by using the returns on assets not used to define these measures.” In other words the α of the fund can be estimated more precisely by including the returns of the non-benchmark assets in the regression, regardless of whether these assets are priced by the benchmarks. The increased precision comes from the correlation between the random components of the passive assets returns and the fund returns. The noise component of the group return and the individual fund return is likely to be positively correlated, and the excess return of the group is likely to be close to zero. Consequently, the estimation of the fund excess return should be improved by adding the group return to the standard set of benchmarks.

Formally let us assume that the individual funds’ errors have the following structure (just one priced risk factor assumed for brevity):

$$r_{i,t}^e = \alpha_i + \beta_i f_t + \epsilon_{i,t}, \tag{9}$$

where

$$\epsilon_{i,t} = \rho_i L_t + \omega_{i,t},$$

and L_t is a zero-mean random variable (not a priced risk factor). Notice, that unlike the case of omitted priced factors, we can obtain unbiased estimates of α_i directly, thus the exercise

is supposed to only increase their precision.

The group return is:

$$r_{g,t}^e = \alpha_g + \beta_g f_t + \epsilon_{g,t}, \quad (10)$$

where

$$\epsilon_{g,t} \equiv \rho_g L_t + \omega_{g,t},$$

or

$$L_t = \frac{\widehat{\epsilon}_{g,t}}{\rho_g} - \frac{\omega_{g,t}}{\rho_g}.$$

Rearranging (10) and substituting the expression for L_t into the model of a single fund, we get:

$$r_{i,t}^e = \alpha_i + \beta_i f_t + \frac{\rho_i}{\rho_g} \widehat{\epsilon}_{g,t} + [\omega_{i,t} - \frac{\rho_i}{\rho_g} \omega_{g,t}]. \quad (11)$$

By estimating (11) together with (10) we can obtain more precise estimates of α_i and β_i for every fund.

II.A.3. Time-Varying Exposure

Assume again a single risk factor model, but now the funds change their exposure to this factor over time.

Following Ferson and Schadt (1996) we represent the excess return of a fund i at time t as:

$$r_{i,t}^e = \alpha_i + \beta_{i,t} f_t + \epsilon_{i,t}, \quad (12)$$

and

$$\beta_{i,t} = \beta_i^0 + k_i Z_t,$$

where f_t is again the single risk factor, β_i^0 is the average exposure of the fund to this risk factor, and $k_i Z_t$ is the time varying component of this exposure by fund i ; $E Z_t = 0$. Again, we are interested in estimating the value of α_i .

Ferson and Schadt (1996) show that by ignoring Z_t one obtains a biased estimate of α_i (if Z_t is correlated with f_t). Usually researchers do not observe Z_t ; to estimate it, Ferson and Schadt (1996) propose various macro factors that may affect the loadings (Avramov

and Wermers (2006) also use similar factors in estimating the excess performance of mutual funds). But if these factors affect the loadings of every fund, then they must also affect the whole group. A parsimonious way to capture the commonalities in loadings across funds is to use the average return of the whole group. The logic is the same as in the omitted factor case, and the net group return serves as an imperfect proxy for the $Z_t f_t$ term.

II.A.4. Predictions

All the econometric models considered above suggest that group return should be used alongside the standard factors to improve the estimates of Jensen's α . In this section we generate predictions that are consistent with the assumptions of the above models.

First, all three models suggest that if one uses the standard risk factors to estimate the α , the estimated residuals should be correlated across groups if the model is applied to group returns, and across funds within a group, if the model is applied to individual funds. If this is the case, then all three models imply that the introduction of the endogenous factor should significantly reduce the correlation between the estimated residuals within group, as it captures common movements in most funds.

Second, all three econometric models suggest that if the average fund in each group has zero excess ability ($\alpha_g = 0$), then by including the endogenous benchmark, we can obtain better estimates of α_i for each fund. Even if this condition is not satisfied, then we estimate the excess ability relative to the group, which is indeed the relevant metric in many applications. While we cannot ascertain which model applies, and whether the estimate is indeed "better", we can make predictions about the explanatory power. The necessary condition for the improvement in estimation is that the endogenous factor's coefficient is significant above and beyond the standard factors.

Finally, the percentage of the significant estimates of α , both positive and negative, should decline following the introduction of the endogenous factor, as the resulting estimate is relative to the overall performance of the group.

In the next sections we test these predictions.

III. Data and Empirical Models

We obtain monthly NAV returns for the universe of U.S. mutual funds from the CRSP Mutual Fund Database for the period 1983-2005. We augment the CRSP investment-objective information with similar information from the mutual fund holdings files obtained from Thomson Financial (since objective information from CRSP is more detailed, but often incomplete), using the MFLINKS of Wharton Research Data Services (WRDS) to link the two datasets. Note that we include all mutual funds that appear in the linked CRSP/Thomson database during a given period, regardless of whether they survive beyond that period.⁶

We examine five equity categories of funds: Aggressive Growth (AG), Growth (G), Growth and Income (GI), Technology (T), and Small Cap Growth (SCG). Table 1 presents counts of mutual funds within each self-declared investment-objective category, at the end of each calendar year. During the early years of our sample period, there are many funds in all groups except Technology (which reaches a reasonable number of funds by 1991).

We also examine eight categories of pure bond funds: Short, Intermediate and Long-Term Government (STG, ITG and LTG), Intermediate and Long-Term Corporate (ITC and LTC), and Short, Intermediate and Long-Term Municipals (STM, ITM and LTM). We form these categories based on asset allocations specified in the CRSP Mutual Fund Database, with the requirement that a fund belongs to a given category only if it invested 70% or more of its assets in that asset category (on average over time). In addition, we define maturity classifications as follows: under 3 years is short term, 3 to 7 years is intermediate term, and greater than 7 years is long term.

Table 1 also shows counts for these bond fund groups. Except for the STM and ITM groups, which only gathered steam by the late 1980's, all groups have many funds throughout the period. This indicates that our group return estimates are precise.

⁶For instance, many of our tests require funds to have 36 months of consecutive return data, but do not require survival beyond that period.

III.A. Equity Fund Models

III.A.1. Baseline Model

We use the Carhart four-factor model as our baseline (reference) model, against which we test our alternative specifications that use endogenous benchmarks. The four-factor model applied to fund or group portfolio i is

$$r_{i,t} = \alpha_i + \beta_{i,rmrf}r_{rmrf,t} + \beta_{i,smb}r_{smb,t} + \beta_{i,hml}r_{hml,t} + \beta_{i,umd}r_{umd,t} + \epsilon_{i,t}, \quad (13)$$

where $r_{i,t}$ is the fund i or equal-weighted group i (we denote this as $r_{g,t}$ in what follows) NAV return, plus 1/12 times the annual expense ratio minus T-bills and $r_{rmrf,t}$, $r_{smb,t}$, $r_{hml,t}$, and $r_{umd,t}$ are the return on the CRSP value-weighted portfolio (NYSE/AMEX/Nasdaq) minus T-bills, and the size, book-to-market, and momentum factor returns (available via Ken French’s website). We run this regression each three years, including only funds with a complete record of NAV returns and expense ratios during this period.

III.A.2. Endogenous Models

Our alternative specification uses the first-stage intercept plus residual of the group return from the four-factor model of Equation (13), $y_{g,t} = \alpha_g + \epsilon_{g,t}$, in a second-stage regression.⁷ In this second stage, we apply the following model to each individual mutual fund within group g :

$$r_{i,t} = \alpha_i + \beta_{i,rmrf}r_{rmrf,t} + \beta_{i,smb}r_{smb,t} + \beta_{i,hml}r_{hml,t} + \beta_{i,umd}r_{umd,t} + \beta_{i,yg,t}y_{g,t} + \epsilon_{i,t}, \quad (14)$$

The regression of Equation (14) helps to control for misspecification in the form of omitted factors or dynamic factor loadings, or for problems with cross-sectionally (across funds) correlated four-factor model residuals.⁸

However, we gain further insight by applying a third model, which relies solely on the endogenous benchmark in a single-factor model:

$$r_{i,t} = \alpha_i + \beta_{i,r_{g,t}}r_{g,t} + \epsilon_{i,t}. \quad (15)$$

⁷To ensure that funds are reasonably assigned to groups, we first omit all funds with an $R^2 < 0.35$ in the regression of the fund return on the group average return during a particular three-year period.

⁸In some specifications we replace the $y_{g,t}$ by the residual from the same equation, $\epsilon_{g,t}$. This way we can compare the estimates gross and net of the group $\alpha_{g,t}$.

This model has the advantage of conserving regression degrees-of-freedom, but will not capture different relative factor loadings among funds. For instance, if some funds hold larger capitalization, low momentum stocks, while others hold smaller capitalization high momentum stocks within the Growth category, then the regression of Equation (15) will perform much worse than the regression of Equation (14). However, it is instructive to determine how well the single endogenous factor model performs in a scenario (i.e., domestic equity funds) where the benchmarks are “tried and true,” to gain insights into how it may perform when the proper benchmarks are not known (e.g., among hedge funds).

III.B. Fixed-Income Fund Models

III.B.1. Baseline Model

Our reference model for bond funds is based on the Blake, Elton, and Gruber six factor model, plus an added equity factor, $RMRF$, which was described in the last section:

$$r_{i,t} = \alpha_i + \beta_{i,IG}r_{IG,t} + \beta_{i,LG}r_{LG,t} + \beta_{i,IC}r_{IC,t} + \beta_{i,LC}r_{LC,t} + \beta_{i,MBS}r_{MBS,t} + \beta_{i,HY}r_{HY,t} + \beta_{i,RMRF}r_{RMRF,t} + \epsilon_{i,t}, \quad (16)$$

where the factors capture risk premia from (1) Intermediate-Term Governments (IG), (2) Long-Term Governments (LG), (3) Intermediate-Term Corporates (IC), (4) Long-Term Corporates (LC), (5) Mortgage-Backed Securities (MBS), High-Yield corporate bonds (HY), and the excess return on the CRSP NYSE/AMEX/Nasdaq portfolio ($RMRF$). Again, we run this regression every three years, including only funds with a complete record of NAV returns and expense ratios during this period. Funds are reassigned to groups, based on their self-declared investment objectives at the beginning of each three-year period.

III.B.2. Endogenous Models

Our alternative specification uses the first-stage intercept plus residual of the group return from the six-factor model of Equation (16), $y_{g,t} = \alpha_g + \epsilon_{g,t}$, in a second-stage regression.⁹ As

⁹Again, to ensure that funds are reasonably assigned to groups, we first omit all funds with an $R^2 < 0.35$ in the regression of the fund return on the group average return during a particular three-year period.

with the equity funds above, we apply the following second-stage model to each individual mutual fund within group g :

$$r_{i,t} = \alpha_i + \beta_{i,IG}r_{IG,t} + \beta_{i,LG}r_{LG,t} + \beta_{i,IC}r_{IC,t} + \beta_{i,LC}r_{LC,t} + \beta_{i,MBS}r_{MBS,t} + \beta_{i,HY}r_{HY,t} + \beta_{i,RMRF}r_{RMRF,t} + \beta_{i,y_{g,t}}y_{g,t} + \epsilon_{i,t}, \quad (17)$$

Our third fixed-income model is:

$$r_{i,t} = \alpha_i + \beta_{i,r_{g,t}}r_{g,t} + \epsilon_{i,t}. \quad (18)$$

IV. Results

IV.A. Fund Groups

IV.A.1. Equity

Most of the extant literature on mutual fund performance has focused on equity funds. A priori, we know that the explanatory power of the standard four-factor model is very high, thus we would expect that adding an additional factor will only make a small contribution to the explanatory power of the model. Nevertheless, since rankings by α can change dramatically with only small model changes, the addition of our endogenous factor may change the relative performance of various funds by removing the additional risk to which these funds are exposed in varying degrees.

We first ask a very simple question: do fund groups on average exhibit excess returns after the standard four risk factors are controlled for. We run regression (13) individually for each of the five equity group returns and estimate the intercept. Table 2 Panel A shows that except for the Growth and Income group, all other equity groups exhibit significant α 's during some periods. In fact, 17 out of 36 estimates in the four remaining groups are significant. Moreover, all the significant estimates for the same period are either positive or negative, depending on the period. This suggests that these estimates do not account for common risks that all funds are exposed to.

We continue with the estimation of the residual correlations across groups. If the four-factor model of Equation (13) adequately explains the returns, then the residuals of the first-

stage regressions are purely random. In such a case our model has no hope of improving the estimation. To test this we compute the across-group correlations between equal-weighted group residuals of the above regressions. Under the null we expect to find correlations that are not significantly different from zero. Panel A of Table 3 shows that this is hardly the case, as we can reject the null of no correlation between group residuals quite frequently: 44 out of 70 possible correlation pairs are positive and significant at the 5% confidence level. Indeed, some of the correlations are extremely high.

For instance, Aggressive Growth funds are highly correlated with Growth, Small Cap Growth, and Technology funds over all three-year periods. Growth is correlated with the Growth and Income, but the latter is not correlated with the Aggressive Growth category. These findings indicate that some important unmodeled common factors are present, but these omitted factors are not common to all funds.¹⁰ It seems that there are at least two independent factors that account for the structure of across-group correlations that we observe.

The above findings suggest that to improve the estimates of the fund’s excess returns, we should control for additional, yet unidentified factors. As these factors are likely to be common to many funds in the group, using the group return is an obvious choice.

IV.A.2. Fixed-Income

Panel B of Table 2 presents the estimates of Jensen’s α using a standard six-factor model. While the estimates are occasionally large relative to the fixed income funds expected returns, most are not significant. Yet, we still observe the same pattern of period-related sign of the α ’s across various groups.

Panel B of Table 3 presents the estimates of the cross-group residuals correlations for the eight fixed-income categories. There are several high correlations between group four-factor residuals. For instance, Intermediate-Term and Long-Term Corporates are highly correlated, and IT and LT Munis are correlated as well. These high correlations indicate that the six-

¹⁰Although there may be some ambiguity with self-identifying as an “aggressive-growth” fund vs. a “growth fund,” we would, nevertheless, not expect widespread similarities between residuals from the four-factor model.

factor model does not capture all of the commonalities in bond fund returns, although the intensity is smaller than in the equities.

The high correlations in equity and bond groups are likely driven by the heavy loadings on the same securities across groups. We conjecture that these loadings can be controlled for using the groups returns.

IV.B. Individual Equity and Fixed-Income Funds

Next we turn to evaluating the performance of the standard models at the individual fund level. Panel A of Table 4 presents the percentage of positive and significant (at the 5% confidence level) pairwise correlations between the individual funds' residuals from the four-factor regressions (Equation 13) out of all possible pairwise correlations in the group (see rows labeled 4-Factor). First, let us notice that the percentage of significant correlations ranges between 20% to 92%, averaging 43% over all time periods. This clearly suggests some common loadings on priced factors, or securities, or common variation in loadings on priced factors over time are present among individual funds within the same group. Clearly, some groups are better modeled by the standard four-factor model than others. For instance, the Growth category is much better modeled than the Technology category, where the average percentage of significant positive correlations is 67%.

Panel B shows a very similar picture for the bond funds using six-factor model. The average proportion of significant correlations is much higher; 61%, and for some groups goes as high as 85%. (e.g., LT Munis). Some categories fit the standard model much better than others.

To illustrate the impact of our methodology, we present the same correlations after including the group return in the regression. For equities, we run the five factor regression of Equation (14) (see the rows labeled "5 Factor"), while for bond funds, we run the seven factor model of Equation (17) (see the rows labeled "7 Factor"). All groups exhibit substantially reduced magnitude of significant pairwise correlations when the group return is added to the standard model. This is true for equity funds (Panel A), where the average proportion of positive significant correlations goes down from 43% to 21%, and for fixed-income funds (Panel B), where the same proportion goes down even further from 61% to 23%. This

clearly indicates that including the group return captures much of the common variation in the individual funds returns. As one would expect, the effect on the traditional groups, where the extant model work well, is lower than the effect on the groups where the standard model does not work well, such as Technology funds or Long-Term Muni funds. In the latter groups adding the endogenous factor makes the biggest difference in reducing the individual fund pairwise correlations.

We interpret the results of Tables 3-4 as evidence that (1) standard factors leave a significant degree of unexplained common covariation among funds within a group and across groups, and (2) a significant part of this covariation can be explained by including an endogenous benchmark (group return) on the individual fund level.¹¹ This provides strong indication that one should include the group return in the performance regressions. Below we show the effect of this inclusion on Jensen’s α estimation.

IV.C. Jensen’s α Estimation

In this section, we present a comparison between different model in terms of their explanatory power and Jensen’s α estimation. First, we compare three models of equities: the traditional four-factor model (Equation (13)), the five-factor model (Equation (14)), and the Endogenous-factor only model (Equation (15)). Panel A of Table 5 presents the results.

The four factor model perform very well in terms of explanatory power, which is not surprising, since much effort was spent to identify factors that explain equity fund returns. In the standard categories - AG, G, GI, and SCG, the adjusted R^2 -squared is 83-89%. In these categories, the marginal addition of the group return is not high – it adds at most 3% to the adjusted R^2 . However, we would like to point out a different set of statistics: the endogenous factor alone (which is tradeable) has an adjusted R^2 between 74% and 84%, which is very high for a model with only a single factor. Moreover, even though the common four factors had been already taken into account, for between 41% to 60% of funds in these four equity categories the coefficient on the net group return is positive and significant at

¹¹We also note that the above results are obtained using fund classification based on the self-declared investment objectives, which could be manipulated. We believe that further gains could likely be made by grouping funds based on commonalities in beginning-of-period holdings or factor loadings.

the 5% level. The Technology group results are different: the returns in this group are less well explained by the four-factors, as indicated by our earlier correlation results, and the R^2 of the group return alone is higher than the R^2 from the four-factor model. For over 85% of funds, the net group return coefficient is positive and significant.

These results indicate that including the group return as a control for unobserved commonalities is useful in all equity funds, but especially in groups that are not well explained by the standard four-factor model, i.e. groups with more specialized investment strategies.

As far as changes in α estimation (the estimate labeled α_2 that is consistent with Equation (14)), the addition of the group return in the most common groups of mutual funds does not substantially change the proportions of funds with positive or negative significant α 's. In most cases the inclusion of the group return reduces the proportion of significant estimates. Notice that this is not the case when we do not control for the level of the group's α (which corresponds to the estimate labeled α_1). In most cases, α 's of the groups are positive, thus removing them reduces the proportion of the significant positive estimates of the excess return on the fund level.

The Technology group again exhibits a different picture: the effects are non-symmetrical for poorly and well performing funds. First, the proportion of funds with positive significant estimates of α decline due to the introduction of the group return. Notice that once we control for the common loadings, the percentage of positive significant estimates of α_1 goes from 11.3% to 19.9%, however, most of it is due to the common loadings on the same stocks. Once these are removed, the proportion goes down to 8.4%. At the same time the proportion of negative significant estimates (funds with really bad abilities) goes up from 2.6% to 8.4%, indicating that there were many really poorly managed Technology funds even when their returns were superior relative to the standard factors.

The next test is presented in Table 6, Panel A. We partition all funds (aggregated across groups) into six buckets based on the size of their t-statistic in the four-factor regression. The buckets contain funds with α 's within one standard deviation from zero (in each direction separately), between one and two standard deviations, and more than two standard deviations. For each bucket, we then compute the percentage of funds that fall in each of the similarly defined buckets using the five-factor model. If the two models correctly identify

the excess ability of fund managers, then we expect to observe high percentages on the diagonal and very low off the diagonal in the table. The results are very different. The largest agreement is for funds that neither model identifies as having ability of any reasonable significance, i.e. those within one standard deviation from zero. It turns out that the only 59.3% (50.6%) of the funds identified in a four-factor model as having significant positive (negative) excess return are given the same identification by the five-factor model.¹² Almost none of the remaining ones switch sign, but many become insignificant. The least agreement is within the category of funds that are identified to have an estimate that is between one and two standard deviations away from zero.

Finally, we compute the rank correlation between the estimates from the two models in a cross-section of funds. The idea is to learn whether the above results are driven by the changes in the relative magnitude of the coefficients obtained in the two models, or by changes in their standard errors. Table 7 Panel A shows that the rank correlations are very high (except for some periods in the Technology group), indicating that the main impact of the group return introduction is on the precision of the estimates, rather on their relative magnitude (rankings).

Panels B of the same tables present the similar evidence for bond funds, using the six-factor model (Equation (16)), the seven-factor model (Equation (17)), and the Endogenous-factor only model (Equation (18)). Panel B of Table 5 shows that while the results for the Corporate and the Government Groups are well-explained by Elton and Gruber's six-factors, the group return is still positive and significant in a large proportion of funds. Indeed, the managers of the Government groups have a rather limited leeway in their investment choices, which is well explained by the loadings on the indices of appropriate duration. In these groups the group return is significant only in about a third of funds, probably due to common variation in loadings over time. In the Corporate groups the percentage of the funds with significant positive loadings on the group return rises to over 60%, and exceeds the percentage of significant loadings for any other explanatory variable. The Muni groups are not well explained by the standard factors, thus the group return alone yields a much

¹²Interestingly, the percentage of funds that are identified as having a significantly positive (negative) excess return by the five-factor model and are also identified by the four-factor model as such as much higher - 79.8% (70.2%). The effect is opposite for the fixed income funds.

higher explanatory power than the six factors. Similarly, the estimates of α change little following the introduction of the group return in the Government and the LT Corporate groups, but very significantly in the IT Corporate and especially in the Muni groups.

Panel B of Table 6 indicates a better agreement between the two models in fixed income funds - but it is far from perfect. Over 20% of all funds identified by the six-factor model as having a significant excess performance (positive and negative separately) are no longer identified as such after the group return is included. Finally, the rank correlations are very close to one, indicating again that the main effect of the group return introduction is not on the relative magnitude of the coefficients, but rather on their standard errors.

Based on these and earlier results we conclude that introducing the group return improves the estimation of the manager's ability in equity and fixed income funds, especially in determining its significance.

IV.D. Out-of-Sample Performance

Our last tests use the endogenous models to form portfolios based on the previous three-year estimates of α , to determine whether the endogenous group factor improves the identification of funds with true skills. We cannot predict a priori whether the introduction of the group return should improve the predictive ability or reduce it, as it has two opposing theoretical effects. On the one hand, the introduction of the group return improves the estimation of the fund's α , thus, if the ability is persistent, the predictive power of the expanded model should improve. On the other hand, as we saw in many cases, the introduction of the group return controls for the risk factors that are not captured by the standard models. If the returns of these unobserved factors are autocorrelated, the introduction of the group return should reduce the predictive power (and correctly so).¹³ Thus we can only estimate the net impact of the two effects and report it.

We start by ranking all funds in a group on their base-model α 's (gross of 1/12 times the expense ratio) over a given 36-month period, and forming equally-weighted quintile

¹³Related, if funds in a group all have skills, then the group benchmark will extract this from each individual fund in the endogenous regressions. However, in this case, our model correctly concludes that we are just as well off investing in the group as in the individual fund.

portfolios. For equity funds, the portfolios are formed separately using the four-factor model and the five-factor model. For fixed-income funds, we use the six-factor model, and the seven factor model.

We then compute the predicted returns on these equally-weighted portfolios over the following 12 months using the loadings on factors that were estimated in the above regression. We then compute the excess return on these portfolios, i.e. the difference between the actual and the predicted returns. Table 8 presents the results three ways: a long investment in the top quintile portfolio, short investment in the bottom quintile portfolio, and the neutral investment that is a difference between the two. We aggregate over all periods, and present the average excess returns and their corresponding standard errors by groups.

Panel A shows the results for equity funds. For the first four categories the results are mixed - the five-factor model shows no significant improvement over the four-factor model. This is perhaps expected as the group return makes relatively little change in the identification of funds with significant excess returns. In the Technology group the picture is different - the four factor model yields no excess returns, while the five-factor model does identify better run funds (but not the badly run ones). The results for the fixed income funds are mixed (see Panel B) and no particular pattern emerges.

We conclude that while we can better estimate the excess return in the fund's historical performance, the improved estimation does not improve the predictive ability on the large fund portfolios. We are currently exploring the impact on the funds that are identified by both models as having superior performance and on those that are disqualified by the extended model.

V. Conclusion

The contribution of this paper is to propose a conceptually simple and easily implementable way to control for economy-wide, and asset-group-wide fluctuations in the markets that affect fund returns. We propose adding the group return, which is endogenous, in addition to the exogenously determined factors in the standard regressions estimating the fund loadings and Jensen's α . This approach has intuitive support, since it represents the investment strategy

that is always feasible for investors. We also show that the group fund is an imperfect proxy (Wooldridge 2002) for the unobserved risk factors, or common loadings on individual securities, that should be added to the regression to improve the estimation. We show that this addition improves the estimation of the Jensen's α under several plausible scenarios found in the literature. We also demonstrate that the effect of this introduction on the

estimates of the excess return in equity and fixed income funds is non-trivial and could change the classification of various managers.

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Summary Statistics

Years	Equities				Bonds					
	Aggressive Growth	Balanced Growth	Growth and Income	Small Cap Growth	Intermed Corp	Long-Term Corp	Intermed Gov't	Long-Term Gov't	Intermed Muni	Long-Term Muni
83 - 86	25	12	30	21	6	21	35	37	14	98
84 - 87	33	10	35	26	8	26	50	61	20	130
85 - 88	41	16	38	39	10	29	62	65	21	153
86 - 89	45	18	42	46	13	31	68	68	25	164
87 - 90	48	23	47	57	15	31	69	73	31	189
88 - 91	53	25	49	57	15	33	85	87	34	219
89 - 92	65	30	54	62	22	40	119	118	46	297
90 - 93	80	26	74	67	34	54	164	158	82	474
91 - 94	88	27	79	69	47	67	202	194	130	659
92 - 95	89	37	108	89	55	76	213	214	146	759
93 - 96	95	54	124	134	65	86	223	230	159	829
94 - 97	113	79	169	188	85	100	228	242	166	864
95 - 98	134	126	348	215	99	124	217	232	177	863
96 - 99	149	140	398	262	119	136	203	219	172	841
97 - 00	148	140	420	322	138	139	206	207	185	829
98 - 01	187	152	452	359	173	138	205	193	189	823
99 - 02	271	159	507	410	197	141	209	197	201	828
00 - 03	356	170	558	475	212	143	216	199	212	817
01 - 04	400	175	626	509	224	146	205	198	218	777
02 - 05	421	179	653	572	250	148	202	216	220	747
03 - 06	406	181	660	662	261	150	204	213	218	761
04 - 07	393	169	634	675	254	146	197	206	211	744

Table 1: This table presents the number of no-load U.S. equity mutual funds and no-load U.S. fixed income mutual funds within each category at each 3 year interval. Funds with multiple shareclasses of the same fund are limited to only a single shareclass in our sample. To be included in the count, a fund must have at least 30 monthly non-missing return observations. Funds are categorized by their self-declared investment objectives.

In-Sample Alpha Estimates

Panel A: Equity Funds

(first row: alpha, second row: t-statistic)

	Period									
	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07	
Agg. Growth	-4.78%	3.51%	3.93%	1.29%	-2.22%	5.51%	-3.46%	1.72%	0.69%	
	-2.78	1.82	2.08	0.81	-1.10	1.47	-2.41	1.91	0.52	
Growth	0.83%	1.62%	1.13%	0.56%	-0.81%	4.09%	-2.20%	1.07%	0.79%	
	1.09	2.58	1.65	0.83	-0.95	2.06	-2.74	1.73	1.22	
Growth & Income	0.49%	0.02%	0.71%	-0.31%	-0.40%	1.52%	-0.30%	-0.49%	0.15%	
	0.59	0.04	1.12	-0.53	-0.76	1.25	-0.55	-1.14	0.62	
Small Cap Growth	0.29%	3.37%	2.13%	0.61%	-1.83%	6.37%	-3.58%	2.36%	1.21%	
	0.27	2.35	1.44	0.50	-1.10	1.67	-2.07	1.99	1.11	
Technology	-22.08%	-4.65%	1.33%	-9.24%	5.26%	16.44%	-3.81%	6.01%	-1.34%	
	-2.72	-0.80	0.25	-1.82	1.05	2.73	-0.73	1.99	-0.33	

Panel B: Bond Funds

	Period									
	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07	
Intermediate	1.62%	-0.91%	0.40%	0.30%	0.33%	0.13%	1.33%	1.17%	0.55%	
	1.18	-1.08	0.34	0.66	0.80	0.28	1.92	1.93	1.91	
Corporate	-0.08%	-1.06%	-0.11%	-0.71%	-0.47%	-0.82%	1.85%	0.84%	-0.07%	
	-0.10	-1.10	-0.10	-0.89	-0.94	-1.65	1.94	0.96	-0.20	
Intermediate	1.82%	-0.73%	-0.28%	-0.44%	0.09%	-0.23%	0.53%	0.02%	0.10%	
	1.38	-1.86	-1.36	-2.10	0.53	-1.68	1.91	0.07	0.34	
Government	-0.12%	0.21%	-0.13%	-0.87%	0.02%	-0.20%	1.43%	0.39%	0.09%	
	-0.14	0.46	-0.37	-2.72	0.07	-0.82	2.31	0.52	0.39	
Intermediate	-0.98%	-1.98%	1.03%	-2.03%	-0.98%	-0.58%	0.10%	0.20%	-0.65%	
	-0.47	-1.77	0.87	-1.26	-1.14	-0.59	0.10	0.22	-1.72	
Municipals	-0.91%	-1.68%	1.35%	-2.37%	-0.61%	-1.10%	1.01%	1.62%	-0.33%	
	-0.28	-0.85	0.66	-0.85	-0.50	-0.66	0.75	1.32	-0.64	

Table 2: This table presents α estimates from equal weighted fund gross excess returns grouped by their investment style. Panel A presents U.S. equity styles and panel B presents U.S. fixed income styles. U.S. equity styles were identified using either ICDI investment codes or S&P style codes in CRSP. Fixed Income styles were identified using allocation, duration, and maturity data in CRSP. Alpha estimates are presented on the first row of each style with the corresponding t-statistics immediately below. Alpha estimates that are significant at the 90% confidence level are presented in bold.

Panel A: Equity Funds

Correlation Coefficients across Group Return Residuals
(first row: correlation, second row: p-value)

Correlation Pairs	Period								
	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07
Agg. Growth and Growth	-0.07 0.66	0.25 0.07	0.58 0.00	0.64 0.00	0.82 0.00	0.95 0.00	0.93 0.00	0.88 0.00	0.74 0.00
Agg Growth and Growth & Income	-0.05 0.61	-0.05 0.61	-0.06 0.63	-0.20 0.88	0.17 0.15	0.31 0.03	-0.31 0.97	-0.07 0.65	0.11 0.26
Agg Growth and Small Cap Growth	0.49 0.00	0.62 0.00	0.90 0.00	0.81 0.00	0.93 0.00	0.98 0.00	0.98 0.00	0.95 0.00	0.88 0.00
Agg Growth and Technology					0.70 0.00	0.61 0.00	0.41 0.01	0.20 0.12	0.47 0.00
Growth and Growth & Income	0.69 0.00	0.57 0.00	0.19 0.14	0.14 0.20	0.28 0.05	0.43 0.00	-0.09 0.70	0.17 0.16	0.37 0.01
Growth and Small Cap Growth	0.29 0.04	0.57 0.00	0.63 0.00	0.79 0.00	0.85 0.00	0.92 0.00	0.94 0.00	0.82 0.00	0.84 0.00
Growth and Technology			0.43 0.00	0.40 0.01	0.64 0.00	0.60 0.00	0.29 0.05	0.09 0.31	0.33 0.02
Growth & Income and Small Cap Growth	0.07 0.34	0.16 0.17	-0.10 0.72	0.06 0.37	0.17 0.15	0.39 0.01	-0.21 0.89	0.03 0.43	0.21 0.11
Growth & Income and Technology			-0.20 0.88	-0.49 1.00	0.08 0.31	-0.23 0.91	-0.61 1.00	-0.52 1.00	-0.22 0.90
Small Cap Growth and Technology			0.51 0.00	0.39 0.01	0.53 0.00	0.48 0.00	0.29 0.04	0.04 0.41	0.33 0.03

Table 3: This table shows the correlation between pairs of mutual fund groups during 3 year subperiods and throughout the sample. Panel A presents equity group categories which include Aggressive Growth, Growth, Growth & Income, Small Cap Growth, and Technology. Panel B presents fixed income group categories which include Intermediate-Term and Long-Term Corporates; Short, Intermediate, and Long-Term Governments; and Short, Intermediate, and Long-Term Municipals. Group returns are defined as the equal-weighted return of all funds in each category. Panel A shows the correlation between group residuals after regressing each group return on the four-factor risk model. ($r_{g,t}^e = \alpha_{1,g} + \gamma_{mkt,g}r_{mkt,t} + \gamma_{hml,g}r_{hml,t} + \gamma_{smb,g}r_{smb,t} + \gamma_{umd,g}r_{umd,t} + \epsilon_{g,t}$). Panel B shows the correlation between group residuals after regressing each group return on a 6 factor risk model based upon Blake, Elton, and Gruber. ($r_{g,t}^e = \alpha_{1,g} + \gamma_{itgov,g}r_{itgov,t} + \gamma_{ltgov,g}r_{ltgov,t} + \gamma_{itcorp,g}r_{itcorp,t} + \gamma_{ltcorp,g}r_{ltcorp,t} + \gamma_{mbs,g}r_{mbs,t} + \gamma_{hy,g}r_{hy,t} + \epsilon_{g,t}$) Numbers in bold are statistically significant at a 90% confidence level.

Panel B: Fixed Income Funds
 Correlation Coefficients across Group Return Residuals
 (first row: correlation, second row: p-value)

Correlation Pairs	Period								
	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07
Intrm Term Corp and Long Term Corp	0.07 0.35	0.83 0.00	0.89 0.00	0.79 0.00	0.81 0.00	0.88 0.00	0.94 0.00	0.97 0.00	0.65 0.00
Intrm Term Corp and Intrm Term Gov't	0.20 0.12	0.04 0.41	-0.15 0.81	0.57 0.00	0.26 0.06	0.08 0.33	0.54 0.00	0.82 0.00	0.22 0.09
Intrm Term Corp and Long Term Gov't	0.24 0.08	0.07 0.34	-0.20 0.88	0.51 0.00	0.02 0.46	0.19 0.13	0.27 0.06	0.55 0.00	0.20 0.12
Long Term Corp and Intrm Term Gov't	0.35 0.02	0.03 0.44	-0.26 0.94	0.66 0.00	0.46 0.00	0.11 0.26	0.63 0.00	0.86 0.00	0.23 0.09
Long Term Corp and Long Term Gov't	0.24 0.08	-0.03 0.56	-0.19 0.87	0.52 0.00	0.28 0.05	0.29 0.04	0.34 0.02	0.56 0.00	0.25 0.07
Intrm Term Gov't and Long Term Gov't	0.83 0.00	0.04 0.41	0.44 0.00	0.52 0.00	0.27 0.05	0.45 0.00	0.74 0.00	0.72 0.00	0.58 0.00
Intrm Term Gov't and Intrm Term Munis	0.01 0.48	0.39 0.01	0.01 0.47	-0.23 0.91	0.09 0.29	0.34 0.02	0.37 0.01	0.45 0.00	0.10 0.28
Intrm Term Gov't and Long Term Munis	0.03 0.44	0.32 0.03	-0.02 0.54	-0.18 0.86	0.13 0.22	0.34 0.02	0.38 0.01	0.48 0.00	0.08 0.32
Long Term Gov't and Intrm Term Munis	0.24 0.08	0.18 0.15	-0.13 0.77	0.01 0.47	-0.03 0.57	0.09 0.30	0.23 0.09	0.34 0.02	0.16 0.17
Long Term Gov't and Long Term Munis	0.29 0.04	0.16 0.18	-0.11 0.74	0.02 0.46	0.02 0.45	0.10 0.29	0.18 0.15	0.29 0.04	0.18 0.15
Intrm Term Munis and Long Term Munis	0.88 0.00	0.92 0.00	0.94 0.00	0.96 0.00	0.96 0.00	0.94 0.00	0.94 0.00	0.97 0.00	0.92 0.00

Panel A: Equity Funds

(percent of funds with significant residual correlations)

Correlation Pairs	Model	Period									
		84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07	
Aggressive Growth	4 Factor	30%	36%	43%	35%	41%	56%	41%	26%	37%	
	5 Factor	17%	19%	15%	18%	18%	20%	20%	16%	20%	
Growth	4 Factor	23%	22%	24%	22%	22%	35%	27%	23%	30%	
	5 Factor	14%	17%	16%	16%	17%	21%	19%	17%	21%	
Growth & Income	4 Factor	27%	20%	25%	25%	23%	38%	33%	32%	36%	
	5 Factor	16%	16%	18%	17%	19%	19%	22%	20%	23%	
Small Cap Growth	4 Factor	27%	38%	33%	31%	37%	61%	53%	35%	44%	
	5 Factor	16%	15%	19%	16%	15%	19%	18%	14%	19%	
Technology	4 Factor	35%	78%	88%	78%	85%	57%	78%	62%	67%	
	5 Factor	14%	33%	38%	56%	17%	22%	24%	17%	25%	
Average	4 Factor	29%	39%	43%	38%	42%	49%	46%	35%	43%	
	5 Factor	15%	20%	21%	24%	17%	20%	20%	17%	21%	

Table 4: This table presents the percentage of funds with statistically significant residual correlations within each group of funds. Panel A of this table presents results for funds in U.S. equity groups after regressing each individual fund's monthly gross excess return on (1) the 4-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{mkt,i} r_{mkt,t} + \gamma_{hml,i} r_{hml,t} + \gamma_{smb,i} r_{smb,t} + \gamma_{umd,i} r_{umd,t} + \epsilon_{i,t}$) and (2) the 4+E factor model. Panel B presents results for funds in U.S. fixed-income groups after regressing each fund's gross excess return on (1) the Blake, Elton, and Gruber 6-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{itgov,i} r_{itgov,t} + \gamma_{ltgov,i} r_{ltgov,t} + \gamma_{itcorp,i} r_{itcorp,t} + \gamma_{ltcorp,i} r_{ltcorp,t} + \gamma_{mbs,i} r_{mbs,t} + \gamma_{hy,i} r_{hy,t} + \epsilon_{i,t}$) and (2) the 6+E factor model.

Panel B: Fixed-Income Funds

(percent of funds with significant residual correlations)

Correlation Pairs	Model	Period								Average
		87-89	90-92	93-95	96-98	99-01	02-04	05-07		
IT Corporates	6 Factor	76%	48%	35%	43%	31%	53%	69%	64%	
	7 Factor	48%	25%	22%	24%	23%	21%	20%	24%	
LT Corporates	6 Factor	48%	52%	43%	34%	33%	71%	90%	55%	
	7 Factor	24%	19%	19%	26%	21%	22%	21%	21%	
IT Governments	6 Factor	28%	28%	24%	23%	26%	66%	81%	43%	
	7 Factor	22%	26%	20%	22%	23%	20%	20%	17%	
LT Governments	6 Factor	31%	31%	26%	29%	25%	66%	76%	40%	
	7 Factor	27%	24%	24%	26%	22%	48%	48%	26%	
IT Munis	6 Factor	83%	94%	97%	98%	98%	97%	96%	81%	
	7 Factor	30%	28%	28%	24%	29%	29%	23%	26%	
LT Munis	6 Factor	96%	98%	99%	100%	100%	100%	100%	85%	
	7 Factor	23%	22%	24%	19%	27%	24%	22%	23%	
Average	6 Factor	60%	58%	54%	54%	52%	75%	85%	61%	
	7 Factor	29%	24%	23%	23%	24%	27%	26%	23%	

Panel A: Equity Funds

	4 Factor Model α (%)	α_1 (%)	α_2 (%)	RMRF	5 Factor Model			UMD	End Factor	Endogenous α (%)	Multi-Endog α (%)
					RMR	HML	SMB				
Aggressive Growth											
Positive Significant	7.4%	10.3%	6.3%	99.6%	18.0%	78.8%	38.2%	60.4%	11.3%	13.0%	
Negative Not Significant	44.3%	41.4%	44.9%	0.2%	16.6%	13.8%	35.2%	29.8%	39.8%	38.1%	
Negative Not Significant	39.9%	36.6%	40.5%	0.0%	24.4%	4.7%	21.9%	8.3%	40.3%	38.0%	
Negative Significant	8.5%	11.7%	8.3%	0.2%	41.0%	2.8%	4.7%	1.5%	8.6%	10.9%	
R^2	88%	90%	90%						84%	86%	
Growth											
Positive Significant	6.1%	7.5%	5.4%	99.9%	27.1%	43.4%	25.0%	41.3%	9.3%	15.3%	
Positive Not Significant	46.2%	44.7%	43.6%	0.1%	21.0%	19.6%	33.1%	40.2%	40.0%	34.0%	
Negative Not Significant	41.4%	39.9%	44.9%	0.0%	23.5%	19.4%	28.8%	16.2%	42.0%	34.4%	
Negative Significant	6.4%	7.9%	6.1%	0.1%	28.5%	17.5%	13.1%	2.3%	8.7%	16.3%	
R^2	88%	90%	90%						80%	87%	
Growth and Income											
Positive Significant	4.1%	5.4%	4.8%	100.0%	50.5%	9.7%	8.9%	47.1%	7.2%	11.2%	
Positive Not Significant	42.0%	40.7%	42.9%	0.0%	22.7%	16.7%	25.4%	39.6%	40.0%	36.0%	
Negative Not Significant	48.6%	47.2%	47.2%	0.0%	18.9%	30.6%	35.9%	11.9%	43.3%	36.9%	
Negative Significant	5.3%	6.8%	5.0%	0.0%	8.0%	42.8%	29.9%	1.4%	9.6%	16.0%	
R-Square	90%	91%	91%						85%	89%	
Small Cap Growth											
Positive Significant	8.1%	11.4%	7.2%	99.9%	21.9%	90.6%	41.7%	69.0%	10.0%	13.0%	
Positive Not Significant	45.4%	42.1%	43.2%	0.2%	21.6%	7.9%	33.8%	25.5%	40.6%	37.8%	
Negative Not Significant	39.7%	36.3%	42.3%	0.0%	27.5%	1.2%	19.6%	5.2%	40.3%	37.5%	
Negative Significant	6.8%	10.2%	7.4%	0.0%	29.0%	0.4%	5.0%	0.4%	9.0%	11.7%	
R^2	87%	90%	90%						85%	89%	
Technology											
Positive Significant	11.3%	19.9%	8.4%	99.8%	1.8%	60.0%	26.4%	85.7%	9.3%	10.7%	
Positive Not Significant	44.1%	35.7%	43.4%	0.2%	2.5%	28.2%	26.1%	9.8%	38.9%	36.9%	
Negative Not Significant	42.0%	32.8%	39.8%	0.0%	9.6%	9.2%	33.9%	4.2%	42.6%	42.0%	
Negative Significant	2.6%	11.6%	8.4%	0.0%	86.1%	2.7%	13.6%	0.4%	9.2%	10.4%	
R^2	83%	90%	90%						88%	91%	

Table 5: This table presents the distribution of coefficient estimates when gross excess fund returns are regressed on risk factor models both with and without an endogenous factor included. Panel A presents U.S. equity fund results under the following models: (1) the 4-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{mkt,i}^T mkt_t + \gamma_{hml,i}^T hml_t + \gamma_{smb,i}^T smb_t + \gamma_{umd,i}^T umd_t + \epsilon_{i,t}$), (2) the 4+E factor where the endogenous factor excludes the group alpha component (α_1), (3) the 4+E factor where the endogenous factor includes the group alpha component (α_2), (4) the E-factor model, and (5) a multi-endogenous model that includes unrelated group factors in the regression. The coefficient significance of the E-factor that corresponds to regressions (2) and (3) is also presented, as are coefficient significance from each of the four standard risk factors. Panel B presents similar results for U.S. fixed income funds. Fixed income gross excess returns are regressed against the following models: (1) the Blake, Elton, and Gruber 6-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{itgov,i}^T itgov_t + \gamma_{itgov,i}^T itgov_t + \gamma_{itcorp,i}^T itcorp_t + \gamma_{itcorp,i}^T itcorp_t + \gamma_{mbs,i}^T mbs_t + \gamma_{hy,i}^T hy_t + \epsilon_{i,t}$), (2) the 6+E factor where the endogenous factor excludes the group alpha component (α_1), (2) the 6+E factor where the endogenous factor includes the group alpha component (α_2), and (4) the E-factor model. As with the equity results, panel B also presents the coefficient significance for each of the risk factor estimates and the endogenous factor estimates that correspond with regression models (2) and (3).

Panel B: Fixed Income Funds

	6-Factor Model α (%)	7 Factor Model							End Factor	Endogenous α (%)	
		α_1 (%)	α_2 (%)	Interm. Gov't	Long Term Gov't	Interm. Corp	Long Term Corp	Mortgages			High Yield
Intermediate Corporate											
Positive Significant	20.0%	27.0%	16.0%	9.4%	12.3%	19.8%	4.5%	9.5%	73.6%	61.4%	16.1%
Positive Not Significant	47.4%	40.4%	37.1%	35.5%	43.8%	44.6%	37.0%	47.8%	15.6%	26.7%	36.6%
Negative Not Significant	28.0%	26.5%	37.8%	40.8%	36.5%	31.4%	47.5%	39.3%	10.2%	9.6%	37.7%
Negative Significant	4.6%	6.1%	9.1%	14.4%	7.3%	4.2%	11.0%	3.4%	0.7%	2.4%	9.6%
R^2	84%	87%	87%								66%
Long-Term Corporate											
Positive Significant	11.4%	16.4%	13.3%	7.3%	16.3%	17.9%	11.1%	11.9%	75.1%	63.1%	11.7%
Positive Not Significant	43.9%	39.0%	41.4%	37.0%	47.0%	41.9%	42.7%	46.2%	17.6%	28.0%	44.4%
Negative Not Significant	36.6%	34.1%	37.4%	43.8%	32.1%	35.0%	40.2%	37.9%	7.0%	8.4%	35.8%
Negative Significant	8.1%	10.4%	7.9%	12.0%	4.7%	5.2%	6.1%	4.0%	0.4%	0.5%	8.2%
R^2	88%	91%	91%								67%
Intermediate Government											
Positive Significant	14.9%	17.0%	15.1%	43.0%	18.1%	9.5%	6.5%	42.4%	5.9%	35.4%	15.4%
Positive Not Significant	44.3%	42.1%	42.5%	35.3%	36.3%	45.9%	42.2%	30.6%	47.4%	46.2%	43.9%
Negative Not Significant	33.4%	32.7%	35.1%	19.9%	33.7%	38.5%	45.0%	22.4%	42.6%	17.4%	31.9%
Negative Significant	7.4%	8.1%	7.4%	1.8%	11.9%	6.1%	6.3%	4.7%	4.0%	0.9%	8.9%
R^2	90%	91%	91%								83%
Long-Term Government											
Positive Significant	8.2%	10.2%	8.2%	21.4%	41.3%	12.9%	5.7%	49.6%	5.2%	33.8%	10.4%
Positive Not Significant	45.2%	43.1%	45.2%	42.1%	36.8%	51.2%	38.8%	28.4%	43.8%	45.6%	46.3%
Negative Not Significant	39.3%	38.5%	40.1%	31.7%	18.8%	31.9%	48.4%	18.0%	44.9%	19.7%	36.6%
Negative Significant	7.3%	8.2%	6.6%	4.8%	3.0%	4.0%	7.1%	4.1%	6.1%	1.0%	6.8%
R^2	89%	91%	91%								81%
Intermediate Muni											
Positive Significant	1.0%	8.3%	15.4%	20.7%	39.3%	45.3%	19.9%	54.4%	35.1%	97.9%	13.0%
Positive Not Significant	27.4%	19.8%	42.3%	20.6%	32.3%	24.4%	34.7%	27.3%	19.6%	1.7%	43.4%
Negative Not Significant	62.3%	29.8%	32.4%	30.8%	23.7%	14.4%	30.9%	12.4%	21.1%	0.4%	31.5%
Negative Significant	9.3%	42.1%	9.9%	28.0%	4.8%	16.0%	14.4%	5.8%	24.3%	0.0%	12.2%
R^2	72%	94%	94%								91%
Long-Term Muni											
Positive Significant	2.2%	18.8%	10.7%	18.1%	58.4%	45.7%	16.2%	57.2%	44.2%	99.6%	12.0%
Positive Not Significant	37.1%	20.3%	48.9%	19.0%	23.8%	20.6%	29.4%	25.7%	16.0%	0.3%	47.0%
Negative Not Significant	59.4%	27.7%	34.0%	26.2%	13.1%	15.2%	32.4%	11.9%	20.0%	0.1%	31.6%
Negative Significant	1.3%	33.3%	6.5%	36.7%	4.8%	18.5%	22.0%	5.2%	19.8%	0.0%	9.4%
R^2	72%	96%	96%								94%

Alpha Significance: Endogenous vs. Non-Endogenous Estimates

Panel A: Pooled Equity Results

4 factor		5 factor α				
α	$-1.645 < t < 0$	$0 < t < 1.645$	$-2 < t < -1.645$	$1.645 < t < 2$	$t < -2$	$t > 2$
$-1.645 < t < 0$	71.7%	17.5%	4.4%	0.7%	4.9%	0.7%
$0 < t < 1.645$	23.7%	71.4%	0.3%	2.7%	0.2%	1.6%
$-2 < t < -1.645$	59.8%	4.1%	19.7%	0.0%	16.4%	0.0%
$1.645 < t < 2$	0.0%	71.5%	0.0%	15.7%	0.0%	12.7%
$t < -2$	32.3%	0.3%	16.9%	0.0%	50.6%	0.0%
$t > 2$	0.0%	18.6%	0.0%	22.1%	0.0%	59.3%

Panel B: Pooled Bond Results

6 factor		7 factor α				
α	$-1.645 < t < 0$	$0 < t < 1.645$	$-2 < t < -1.645$	$1.645 < t < 2$	$t < -2$	$t > 2$
$-1.645 < t < 0$	43.5%	39.9%	3.5%	3.5%	5.3%	4.3%
$0 < t < 1.645$	25.3%	56.2%	1.0%	6.0%	0.5%	11.0%
$-2 < t < -1.645$	28.6%	0.0%	24.4%	0.0%	47.1%	0.0%
$1.645 < t < 2$	0.0%	46.4%	0.0%	24.4%	0.0%	29.2%
$t < -2$	8.8%	0.4%	12.3%	0.0%	78.4%	0.0%
$t > 2$	0.0%	14.3%	0.0%	6.2%	0.0%	79.5%

Table 6: This table presents the percentage of statistically significant alpha estimates in the 4 factor and the 4 plus endogenous factor model regressions. Each value in position (i, j) reflects the percent of alpha estimates with 4 factor significance row i that have 4+endogenous factor significance j . Row percentages sum to 100%. This table shows that statistically insignificant alpha estimates tend to show insignificance in both estimation models as do strongly significant alpha estimates. Alpha estimates with 4 factor t-statistics that are weakly significant $(1.645 < |t| < 2)$, tend to change in the 4+endogenous estimations to either insignificant or strongly significant. Panel A presents results for equities while panel B present bond results.

Alpha Rank Correlations
4 Factor Estimates vs. 4+e Factor Estimates
Panel A: Equity Funds

	(first row: alpha, second row: p-value)									
	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07	
All Equity	0.94	0.88	0.92	0.98	0.96	0.87	0.80	0.87	0.79	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Agg. Growth	0.90	0.88	0.90	0.97	0.95	0.92	0.81	0.93	0.75	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Growth	0.98	0.88	0.93	0.99	0.98	0.86	0.76	0.89	0.78	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Growth & Income	0.99	1.00	0.97	0.99	0.99	0.94	0.98	0.98	0.94	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Small Cap Growth	0.99	0.90	0.95	0.98	0.96	0.92	0.90	0.92	0.73	
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Technology	NA	NA	NA	NA	0.95	0.60	0.90	0.86	0.55	
	NA	NA	NA	NA	0.00	0.00	0.00	0.00	0.00	

Table 7: This table presents the rank correlations between non-endogenous model and endogenous model in-sample estimates of alpha. The results for each group are detailed on two lines where the first line contains the estimated rank correlation while the second line contains the correlation p-value. Equity model estimates are presented in panel A while fixed income estimates are presented in panel B. Numbers in bold are significant at the 90% confidence level.

Alpha Rank Correlations
6 Factor Estimates vs. 6+e Factor Estimates
Panel B: Bond Funds

	84-86	87-89	90-92	93-95	96-98	99-01	02-04	05-07	84-07
All Bonds	0.84	0.81	0.90	0.81	0.87	0.88	0.84	0.75	0.61
	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Intermediate	0.96	0.93	0.98	0.99	0.98	0.99	0.94	0.92	0.89
Corporate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long-Term	0.99	0.94	0.99	0.98	0.98	0.97	0.96	0.98	0.83
Corporate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Intermediate	0.88	0.92	0.98	0.97	1.00	0.97	0.94	0.99	0.90
Government	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long-Term	0.97	0.99	0.99	0.92	1.00	0.99	0.91	0.99	0.91
Government	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Intermediate	0.94	0.85	0.95	0.92	0.95	0.95	0.96	0.97	0.73
Municipals	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long-Term	0.86	0.80	0.98	0.95	0.98	0.94	0.98	0.98	0.43
Municipals	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Panel A: Equity Funds

Group	Model	Avg.		
		Return (%)	T-Stat	
Aggressive	Neutral 4 factors	3.09	2.74	
Growth	Neutral 5f (no α_g)	2.46	1.21	
	Neutral 5 factors	2.80	2.98	
	Long 4 factors	1.11	0.78	
	Long 5f (no α_g)	3.93	1.04	
	Long 5 factors	3.40	0.87	
	Short 4 factors	-1.97	-2.54	
	Short 5f (no α_g)	1.47	0.41	
	Short 5 factors	0.61	0.16	
	Growth & Income	Neutral 4 factors	2.83	5.50
		Neutral 5f (no α_g)	3.98	5.03
		Neutral 5 factors	1.55	1.06
		Long 4 factors	1.44	1.91
		Long 5f (no α_g)	3.25	1.39
		Long 5 factors	1.34	0.90
Short 4 factors		-1.39	-3.01	
Short 5f (no α_g)		-0.73	-0.30	
Short 5 factors		-0.21	-0.08	
Small Cap Growth		Neutral 4 factors	2.03	3.94
	Neutral 5f (no α_g)	2.06	3.53	
	Neutral 5 factors	2.80	6.30	
	Long 4 factors	1.15	2.19	
	Long 5f (no α_g)	1.25	1.22	
	Long 5 factors	1.47	1.22	
	Short 4 factors	-0.88	-2.20	
	Short 5f (no α_g)	-0.81	-0.66	
	Short 5 factors	-1.33	-1.14	
	Technology	Neutral 4 factors	3.77	4.49
		Neutral 5f (no α_g)	4.13	3.64
		Neutral 5 factors	3.98	3.59
		Long 4 factors	2.10	1.83
		Long 5f (no α_g)	3.04	2.25
Long 5 factors		2.01	1.71	
Short 4 factors		-1.67	-2.02	
Short 5f (no α_g)		-1.09	-0.76	
Short 5 factors		-1.97	-1.35	
Technology		Neutral 4 factors	0.74	0.30
	Neutral 5f (no α_g)	9.48	2.44	
	Neutral 5 factors	2.55	0.91	
	Long 4 factors	5.17	1.26	
	Long 5f (no α_g)	10.45	1.97	
	Long 5 factors	3.48	2.43	
	Short 4 factors	4.43	0.90	
	Short 5f (no α_g)	0.96	0.39	
	Short 5 factors	0.93	0.23	

Table 8: Panel A of this table presents time-series out-of-sample alpha estimates from January 1987 through June 2007 for the equal-weighted portfolio of funds that are constructed on the alpha from (1) the 4-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{mkt,i} r_{mkt,t} + \gamma_{hml,i} r_{hml,t} + \gamma_{smb,i} r_{smb,t} + \gamma_{umd,i} r_{umd,t} + \epsilon_{i,t}$), from (2) the 4+E factor model when the endogenous factor excludes the group's average alpha (correlated errors or time varying factors model), and from (3) the 4+E factor model when the endogenous factor includes the group's average alpha (omitted variable model). Panel B presents the same for (1) the Blake, Elton, and Gruber 6-factor model ($r_{i,t}^e = \alpha_{1,i} + \gamma_{itgov,i} r_{itgov,t} + \gamma_{ltgov,i} r_{ltgov,t} + \gamma_{itcorp,i} r_{itcorp,t} + \gamma_{ltcorp,i} r_{ltcorp,t} + \gamma_{mbs,i} r_{mbs,t} + \gamma_{hy,i} r_{hy,t} + \epsilon_{i,t}$), (2) the 6+E factor model when the endogenous factor excludes the group's average alpha (correlated errors or time varying factors), and (3) the 6+E factor model when the endogenous factor includes the group's average alpha (omitted variables model). In each category, funds are ranked during each three-year time-period on their alphas, then quintile portfolios are formed. Out-of-sample alpha estimates are then calculated as the realized performance less predicted performance (intercept omitted) over the subsequent 12 months. Mean and standard errors of overlapping observations were calculated following Jegadeesh (1997). The data represent a Neutral investment (investment in top quintile funds less investment in bottom quintile funds), long-only investment (investment in top quintile funds), and short-only investment (investment in bottom quintile funds). Statistically significant alpha estimates are shown in bold. Equity investment objective groups include: Aggressive Growth, Growth, Growth & Income, Small Cap Growth. Fixed Income investment objective groups include: Intermediate, and Long Term Governments; Intermediate and Long Term Corporates; and Intermediate, and Long Term Munis.

Panel B: Fixed-Income Funds

Group	Model	Avg. Return (%)	T-Stat
Intermediate	Neutral 6 factors	1.03	1.05
Corporate	Neutral 7f (no α_g)	2.68	1.95
	Neutral 7 factors	1.21	1.36
	Long 6 factors	1.33	4.45
	Long 7f (no α_g)	0.77	1.12
	Long 7 factors	0.26	0.32
	Short 6 factors	0.29	0.36
	Short 7f (no α_g)	-1.91	-1.04
	Short 7 factors	-0.95	-0.92
Long	Neutral 6 factors	1.63	5.71
Corporate	Neutral 7f (no α_g)	2.89	4.28
	Neutral 7 factors	1.83	3.56
	Long 6 factors	1.03	2.24
	Long 7f (no α_g)	0.47	0.41
	Long 7 factors	0.42	0.29
	Short 6 factors	-0.60	-1.33
	Short 7f (no α_g)	-2.41	-1.73
	Short 7 factors	-1.41	-1.30
Intermediate Government	Neutral 6 factors	0.89	3.26
	Neutral 7f (no α_g)	2.02	4.20
	Neutral 7 factors	1.61	5.46
	Long 6 factors	0.41	2.85
	Long 7f (no α_g)	-0.18	-0.46
	Long 7 factors	-0.15	-0.33
	Short 6 factors	-0.49	-2.32
	Short 7f (no α_g)	-2.20	-3.04
Long Government	Short 7 factors	-1.75	-3.27
	Neutral 6 factors	1.00	2.79
	Neutral 7f (no α_g)	0.77	2.45
	Neutral 7 factors	1.02	3.11
	Long 6 factors	0.75	2.92
	Long 7f (no α_g)	0.50	1.17
	Long 7 factors	0.82	2.24
	Short 6 factors	-0.25	-1.27
Intermediate Municipal	Short 7f (no α_g)	-0.27	-0.83
	Short 7 factors	-0.20	-0.57
	Neutral 6 factors	0.72	2.35
	Neutral 7f (no α_g)	0.40	1.53
	Neutral 7 factors	0.40	1.21
	Long 6 factors	-0.08	-0.19
	Long 7f (no α_g)	-1.60	-2.82
	Long 7 factors	-0.40	-1.04
Long Municipal	Short 6 factors	-0.80	-2.22
	Short 7f (no α_g)	-1.99	-4.07
	Short 7 factors	-0.80	-3.10
	Neutral 6 factors	0.67	3.20
	Neutral 7f (no α_g)	0.65	2.77
	Neutral 7 factors	0.62	3.17
	Long 6 factors	0.18	0.33
	Long 7f (no α_g)	-0.48	-1.11
Long Municipal	Long 7 factors	0.55	1.57
	Short 6 factors	-0.49	-0.79
	Short 7f (no α_g)	-1.13	-2.30
	Short 7 factors	-0.07	-0.20

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