COMMON FACTORS IN ACTIVE AND PASSIVE PORTFOLIOS

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A great deal of the literature in financial economics contains the assumption that returns are a linear function of a set of observable or unobservable factors. The specification of the variables in the linear process (known as the return-generating process) is one of the key issues in finance today.

The return-generating process is an important building block in asset pricing models, portfolio optimization, risk management models, mutual fund evaluation, and event studies. For many purposes (such as in developing asset pricing models and evaluating mutual fund performance), it is important to separate systematic from non-systematic factors. There have been numerous attempts to examine the number and type of systematic factors in equity returns.

Approaches to identifying the return-generating process include purely statistical models such as those of Connor & Korajczyk (1986), Dhrymes, Friend & Gultekin (1984), Elton and Gruber (1984), Roll and Ross (1980), and Lehmann and Modest (1988), and models that a priori specify and test a set of fundamental factors and/or portfolios such as those of Chen, Roll and Ross (1986), Fama and French (1992, 1993), and Burmeister, et al. (1986, 1987 and 1994).[1]

The purpose of this study is to determine systematic factors by examining mutual

[1] Another version referred to as conditional asset pricing uses the return on a set of *a priori* selected portfolios as multiplied by lagged instruments. See Hansen and Jagannathan (1991), Cochran (1996), and Ferson and Schadt (1996).

fund returns. There is a reason stemming from modern portfolio theory why it might be informative to work with mutual fund returns in addition to either security returns or portfolios of security returns constructed on a mechanical basis. One important implication of modern portfolio theory is that, given a belief about systematic factors, an investor should select an exposure (beta) to each factor, a level of expected risk-adjusted return (alpha) and a level of residual risk (residual variance).[2] The mutual fund industry has an incentive to offer an array of exposures to systematic factors in order to span investors' differing objective functions. If mutual funds all choose similar sensitivities to a factor, a mutual fund deviating from the norm should attract substantial investor interest and cash inflow. Thus, investors' objectives and mutual funds' incentives should result in a spread of sensitivities to factors viewed as systematic by investors. In addition, mutual funds are real portfolios that are feasible for investors to hold and are traded at real prices. Therefore, mutual funds provide a logical way to obtain portfolios which have a spread on the characteristics of interest to investors while smoothing much of the noise inherent when a model is fitted to individual security returns. Finally, employing mutual fund data, rather than forming portfolios of securities directly, avoids having to pre-specify the relevant characteristics and as shown later leads to better separation of the sensitivities than forming portfolios on the basis of a proxy characteristic (e.g. size).

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[2] See, for example, Elton and Gruber (1992) or Fama (1993).

There are two ancillary benefits of studying mutual funds. First, studying mutual funds gives us a convenient holdout sample. We test the return generating process developed from mutual fund data on common stocks formed into passive portfolios, first on the basis of industry membership (using SIC codes), and then on the basis of size. This allows us to see whether our results are unique to actively managed portfolios or have wider implications for capital markets.[3] The second benefit concerns the study of mutual fund performance. To examine mutual fund performance in a meaningful way, one needs to specify a return-generating process. Much of the literature uses an assumed return-generating process to evaluate mutual funds. What better way to find the systematic influences that affect mutual funds than by studying mutual funds themselves?

The use of mutual funds has some disadvantages. First, in common with other grouping procedures, there are fewer cross-sectional observations than would be available using individual securities. However, our sample size is much larger than those employed by others who have used portfolios. Second, there is a possibility that some sort of common dynamic behavior (such as herding or momentum investing) could lead to finding a factor that is not present in stock returns. Third, there is a possibility that mutual funds avoid securities with sensitivity to a factor. Fourth, the presence of common holdings across funds might lead to misidentifying factors. These concerns are explored

[3] This approach started with Jensen's (1966) early work (which assumed a one-index return-generating process) up through the work of Elton, Gruber & Blake (1996a), which assumed a four-index model. As shown in Elton, Gruber, Das & Hlavka (1993), the choice of the return-generating process can affect the performance

in some detail later in the paper. In particular, we deal with the problem of common holdings explicitly, and we include a section testing our model on common stocks. This sample is free from the potential problem of common holdings and the impact of dynamic trading strategies. Furthermore, if we miss a factor because it is not present in mutual fund returns, this should simply result in our model not working well for common stock returns.

This paper is organized as follows: In the first section we discuss the samples we use to analyze the return-generating process. In the second section we present our analysis and tests of alternative four- and five-index models on mutual fund data. In the third section we test the models we have developed on passive portfolios of common stocks to demonstrate that the results are not restricted to mutual funds.

I. SAMPLE

We use data on mutual funds and indexes in this study. All mutual fund data were supplied by Micropal.[4] We initially selected all mutual funds that existed as of January 1979 and that had monthly return data through December 1993. Such a sample clearly has survivorship bias, but for the purposes of determining the important factors affecting

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attributed to management.

[4] The accuracy of the data is discussed in Elton, Gruber and Blake (1996b). Micropal is a successor firm to Investment Company Data Inc.

returns, survivorship bias should be unimportant.[5] There were 351 funds (excluding money market and municipal bond funds) that existed in the Micropal database over this period. From this data set we eliminated bond, option, precious metal, international, and index funds. We selected this set of plain-vanilla stock funds because we are searching for factors (indexes) that are important in explaining the returns on common stocks. We might well have uncovered other factors if we had included funds which held foreign stocks or only bonds, but that would go well beyond the intended scope of this study. Our sample design is analogous to that of most of the empirical literature on APT, which does not include stocks traded on foreign exchanges or bonds in forming portfolios for testing purposes. To the extent that we miss important influences by excluding types of funds, our model should produce less than satisfactory results when tested on passive portfolios. This left us with a set of 267 funds. We divided these funds into three 89-fund subsamples (group A, group B and group C). Having multiple samples allows us to test the robustness of results and in particular to see whether results derived on one set of data are generally applicable.

The three subsamples were selected so that each subsample had the same number of funds with a given objective and so that funds from any fund family (e.g. Fidelity)

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[5] A problem would result only if funds which did not survive were the only funds affected by some factor so that this factor would not be uncovered in this study. We tested this and found no significant difference between the survivor sample and non-survivor sample (see later discussion).

were spread evenly across the three groups. Having the same number of funds with a given objective in each group makes the subsamples reflective of the overall distribution of objectives. Spreading any fund family across all groups helps to ensure that the factors we pick up are not associated with a fund family's style. By using three separate samples we are able to examine whether the results are statistically significant in each subsample as well as the total sample, and whether the ordering of models is robust across samples.

The indexes we use fall into two groups: those that are publicly available, such as the S&P 500 index, and those that we constructed from other publicly available data bases. We will discuss the detailed construction and characteristics of these indexes in later sections. In addition, we use data on two sets of passive portfolios in this study. The return data for the securities used to construct these portfolios came from CRSP.

II. ANALYSIS

A multi-index model that captures all of the relevant influences that explain why securities move together should have a diagonal variance/covariance or correlation matrix (all correlations between securities equal zero) and should have non-zero betas on each index for many assets. We will employ tests to determine if both of these conditions are met.

The correlation between security returns is generally positive for all pairs of assets. However, once the market index is removed, some pairwise correlations of residuals are usually negative, while some are positive. The average correlation could be zero, while each individual correlation could be large in absolute value and thus very different from zero. Furthermore, adding a systematic index that significantly explains returns can cause the average correlation to increase, decrease or remain constant.

How might we measure closeness to zero when some observations are positive and some negative? One measure is to take the average absolute value of the correlation. This has the property that if a model results in correlations being closer to zero, it is reflected in the metric.[6] If we find that one model produces on average lower absolute values of correlations than does another model, and if this difference is statistically significant, we have evidence that this model is a superior explanation of the return generating process.[7] We also examine the entire distribution of the absolute value residual correlations between funds for each model. If, in addition to having a lower average, a model has fewer large correlations for each of a number of preselected values, we have further evidence of that model's superiority.

The last set of tests we perform to judge significance involves an examination of the coefficients in a time series equation relating the return on each portfolio to the returns on the indexes for each of our models. More specifically, we examine the number of times

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[6] There are a number of direct tests that a variance/covariance matrix is diagonal. These are in the factor analysis literature. The best known is the Bartlet test, which uses the square of the residual correlation to eliminate the sign problem rather than the absolute value of the residual correlations of the measure we use. However, even the proponents of these tests suggest the single valued test statistic is at best a rough guide relative to looking at the distribution of covariance (Lawley & Maxwell (1963)).

[7] We also report the average residual correlation (as opposed to the average absolute value residual correlation) for each model.

the sensitivity to each index (beta) is significantly different from zero. If the ranking on all these tests if the same, we have strong evidence that one model outperforms the other as a candidate for the return generating process.

In what follows, we will use the average absolute value correlation of residuals, the distribution of absolute value correlations, and the significance of betas as tests for differentiating between alternative return generating processes..

A. The Base Model

In this section we present some results from what we call our base model. We use this model as a standard against which to judge more complex models. The base model we employ consists of four indexes. Many of the articles concerning return generating and APT models have found evidence of four or five indexes (although some authors detect the possible evidence of a sixth index). Before we proceed to examine the possible existence of a fifth or sixth index, we must explore whether indexes in a particular four-index model are themselves significant. In this section after exploring the performance of the base model we will examine the distribution of mutual fund sensitivities to these indexes as evidence that mutual funds constitute a reasonable set of portfolios on which to study return-generating processes.

Table 1 and Table 2 present these results for a number of different models. Let's start by examining Panel A of Table 1. Panel A presents results based on the absolute values of the correlations between residuals for a standard one-index model and a four-index model (called the "base" model) that we have employed in previous research.

The one-index model uses the excess return on the CRSP SBBI S&P 500 total return index as the single index. The base four-index model adds to the S&P 500 index (measured in excess-return form): (1) a bond market index (a par-weighted combination of the Lehman Brothers aggregate bond index and the Blume/Keim high-yield bond index in excess-return form); (2) a small-cap minus large-cap index (the average of the Prudential-Bache small-cap growth and value indexes minus the average of their large-cap growth and value indexes); (3) a growth minus value index (the average of the Prudential-Bache large-, mid- and small-cap growth indexes minus the average of their large-, mid- and small-cap value indexes).

The S&P 500 total return index and the small minus large index were selected because they have been shown to be related to security returns in a number of studies. Growth minus value was selected as the third index in our base model. Both growth minus value and market-to-book have been shown to be importantly related to security returns. However, because growth minus value is highly correlated with returns on portfolios separated by their market-to-book ratio, we included only one of the indexes. Shortly we will discuss both the market-to-book and growth minus value indexes to gain insight into which is the more fundamental index. A bond index was included because a number of authors have found bond indexes to be related to returns (see Burmeister et al (1987) and Fama & French (1993)). In this and later sections we will test the importance of the base index in explaining both mutual fund and security returns.

We use the four-index model as our base model. We performed (but do not report) tests to see if the four-index model outperforms models using any combination of subsets of the indexes. The four-index model reduces residual correlation at a statistically significant level from a model employing any possible combination of these indexes taken two or three at a time.

As shown in Panel A of Table 1, the mean absolute value of the residual correlations (as well as the average residual correlation) becomes smaller as we move from the one-index model to the base four-index model. The means are statistically different using a simple *t* test. Of more importance, the base model dominates the single-index model using first-order stochastic dominance. First order stochastic dominance examines the cumulative distribution. If, for every size error, one model always has a larger number of errors equal to or smaller than the selected **size** error, first order stochastic dominance exists.[8] The logic is that under any weighting scheme the model with more small errors will be superior as long as large errors are weighted more heavily than small. This is a particularly powerful test, since it does not depend on the choice of a weighting scheme of correlations (e.g., squared correlations or average correlations).

Finally, examining Table 2 shows that both the betas on the S&P index and the small

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[8] For reasons of space, we show only the distribution for a selected number of points in Table 1.

minus large index are significantly different from zero at the 5% level for almost all funds, while the sensitivities on the Growth minus Value index and bond index are significant for 74% and 47% of the funds respectively. This is clearly much larger than the 5% that would be expected by chance.

Since the four-index model outperforms the single-index model (and in fact models with fewer indexes) for each of our groups, the question remains as to whether we can find a fifth index which is important in the return generating process. Before we turn to this question, let us examine the spread in sensitivities of the funds in our sample to each of the indexes in our model. As discussed earlier, a justification for using mutual fund data is a belief that we will get a substantial spread on sensitivities. To judge this, we need a comparison group. Since size is often used as a criterion for forming portfolios to test return-generating processes, we selected the size deciles from the monthly CRSP Stock Indices file as an alternative set of portfolios with which to judge the dispersion of sensitivities. Table 3 presents the standard deviation of sensitivities and the difference in the 20th and 80th deciles for our full sample of mutual funds as well as for the CRSP deciles.[9] These dispersions are shown for our base four-index model and three candidates for a fifth index introduced later. It is clear from this table that mutual funds not only show dispersion on the sensitivities to each index, but also (with two exceptions) they

[9] We make comparisons using standard deviation and percentiles, since these measures are not affected by sample size and the sample sizes are different in the groups being compared.

show more dispersion than the CRSP size deciles. The main exception is the sensitivity to the size index. This is logical, since the CRSP deciles were selected to maximize dispersion on this index. However, even here the mutual funds show a high degree of dispersion consistent with the dispersion of mutual fund sensitivities on other indexes. Mutual funds are presenting investors with alternative sensitivities to the indexes in our model, and mutual funds thus present a meaningful way to examine a return-generating process.

B. A Fifth Index

In this section we explore whether a fifth index should be added to the base model. The first candidate we examine for a fifth index is derived from the data itself. For each group we performed a maximum-likelihood factor analysis on the residuals from the base (four-index) model and extracted the one-factor solution. For any group, this represents the best index that can be found for explaining the residual covariances for that group. However, the factor will pick up influences that may be unique to the group from which it is extracted, as well as more general systematic influences. To eliminate the effect of unique influences, the factor derived from group A was used to explain the correlation in group B, the factor from B to explain C, and the factor from C to explain A.

As shown in panel A of Table 1, when the fifth index is extracted via factor analysis, there is a very large improvement in the residual correlation estimates. The results show stochastic dominance over the four-index model, and the difference in the average absolute values of the correlation coefficients is significant at the .01 level. In addition, when we examine Table 2, more than 71% of the funds have a significant sensitivity (at the 5% level) on the fifth factor.

The question remains as to whether we can find an alternative fifth index that works as well or better than the factor approximation and that has an economic meaning. We tried three alternative factors that have been suggested in the literature or are suggested from the analysis: a sentiment index, a momentum index, and an index based on the performance of growth mutual funds.[10]

The first pre-specified factor we tried is the sentiment index developed by Lee, Schleifer and Thaler (1991). They have argued that the change in the discounts of closed end mutual funds reflects investor sentiment, and that this index systematically affects stock returns and should be priced. Since our time frame differs from theirs, we needed to construct our own version of their index. We followed the exact procedure they described except that we include new funds six months after issuance and delete funds three months before they disappear, because of the well-documented effect on returns of these two events. We regressed the sentiment index on our base model, and used the residuals as our

[10] We tried one other approach. We formed portfolios of stocks that represented sectors of the economy. We examined a financial sector, a utility sector, a high-tech sector, metals stocks, foreign stocks, and a natural resource sector. These were selected because of their inclusion in other studies. None of the five-index models using a sector factor outperformed the four-index base model at a significant level, and all were outperformed by the five-index model containing a f actor (base model plus factor) at the .01 level of significance. In the interest of space, we do not show these results in the tables.

fifth index.[11] Examining the absolute value of the correlations in Table 1, Panel B showed that sentiment did not add to the explanation of the correlation when added as a fifth index. When we examine the number of significant betas for our fund sample (Table 2), we observe only a few more significant betas than one would expect by chance. Sentiment does not seem to be a reasonable fifth index.

The second index we examined was the momentum index suggested by Jegadeesh and Titman (1993) and Werners (1996). We used the form of the index from Carhart (1997)[12]. Their index was orthogonalized to our four-index model so that the marginal effect of momentum could be examined. Examining Table 1 shows that the momentum index does reduce both the average and average absolute residual correlation compared to the four-index model. Furthermore, the distribution of the absolute correlations coefficients shows stochastic dominance for all three samples. The momentum index seems to be adding information. However, when we compare the momentum index to the use of the factor solution as the fifth index, momentum doesn’t fare as well. When it is used (compared to the factor solution) both the absolute value of the average and the average correlations are higher and the factor solution shows stochastic dominance in two out of three cases. When we examine the regression estimate (Table 2) we find similar

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[11] Sentiment was related to size and value growth. Sentiment may be an explanation for either of these indexes entering. In this paper we are testing whether it has any independent influence.

[12] We thank Carhart for supplying us with the index which he computed.

results. The beta on the momentum index is significant 48% of the time, while the beta associated with the factor is significant 72% of the time. Once again, momentum seems to be adding information as a fifth index, but it adds much less information than can be obtained by a fifth factor index.

Since neither of these indexes appears to be an important fifth factor, we decided to examine an index which represented mutual fund returns themselves rather than security returns. We selected the Morningstar growth mutual fund index (an equally weighted index of the funds Morningstar classifies as growth) as our fifth index. This growth index was selected because this is our largest category of funds and because residuals from the four-index model are smaller for income funds than they are for growth and aggressive growth funds. We reformulated the Morningstar index by regressing it against the four-index base model and used the residuals as our mutual fund growth index, which we refer to as MGO.

The first fact to notice from Panel B of Table 1 is that the introduction of the mutual fund growth index (MGO) results in a model which outperforms the four-index base model (the difference in average absolute values is statistically significant level at the .01 level). Furthermore, from Table 2, 72% of the betas are significantly different from zero. When we compare the five-index model using the mutual fund growth index to the model using the factor as the fifth index, we find that the results are virtually indistinguishable.[13] No technique shows stochastic dominance over the other in any of the three samples, the mean differences in absolute values of correlation coefficients are not statistically different, and the number of betas that are significant is identical. Furthermore, the mutual fund growth index is highly correlated with the factor extracted by factor analysis. The correlation between the factor scores and the growth index is .86, .88 and .82 for the three samples we examined.

It is worthwhile comparing the performance of the MGO index with the performance of the momentum index, for the momentum index did show some explanatory power. The indexes are not completely different, but they are certainly not redundant. The simple correlation between the two indexes is .37.

When we compare their performance in Table 1 we see that in each sample MGO produces a lower average absolute correlation coefficient and a lower average correlation than does the momentum index. The different is statistically significant at the 5% level in all three samples, and MGO has errors which are stochastically dominant in two of the three samples.

When we examine the regression analysis in Table 2, the results are even clearer. The beta in MGO is statistically significantly different from zero 72% of the time compared to 48% for momentum. When both indexes are entered in the regression

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[13] It would not be surprising to find the factor related to an equally weighted index of all mutual funds, given the nature of factor analysis. However, it is surprising to find that the factor is so highly related to an equally weighted combination of a subset of the funds which constitutes about 40% of our sample and which has particular

together (as the fifth and sixth index), the MGO is significant 69% of the time while momentum is significant 31% of the time. When residuals are examined as in Table 1, the results using the six-index model are not different from the results using MGO as the fifth index in a five-index model, and better at a significant level than the results using momentum as the fifth index. The results clearly indicate that while for mutual funds momentum may have some explanatory power, it is clearly dominated by the use of MGO as a fifth index.[14] Since a mutual fund growth index improves results and is economically identifiable, it is worthwhile to try to understand why it enters and what its relationship is to the growth-minus-value index in our base four-index model.

The base four-index model includes the difference between a growth and a value index as one of the indexes. One possibility for the improvement of adding the mutual fund growth index is that when we use the difference in growth and value we are implicitly assuming they are equally important. Perhaps the five-index model leads to improvement because an unequal combination of the Prudential Bache growth and value indexes represents the factor affecting returns. This can be tested by adding either the Prudential-Bache value or growth index to our base four-index model. When we did this,

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characteristics different from the other funds.

[14] There is some concern that survivorship could affect our results. To test this we constructed a sample of funds that merged over our sample period, and thus would not be in our sample. These funds are an exhaustive set of funds that existed as of 1977, had at least five years of history, and disappeared (merged). We compared the average absolute correlation of the residuals over the period they existed with the average absolute value for the funds that did not disappear. The difference between the sample of merged funds and the survivor sample was insignificant. We similarly examined the pattern of significant betas. In all cases the merger sample and the survived sample was within two betas of having the same proportion of significant betas. This supports that there is no difference in the

the results were not improved over the base four-index model. A second possibility is the base model could be improved by a better formulation of the growth-value variable.

There are two generic types of value and growth indexes. One type classifies firms into portfolios on the basis of high or low values on a multiple set of characteristics such as earnings price ratios, forecasted earnings growth, divided yields, etc. (e.g., Prudential Bache and Wilshire use this approach). The second type uses a single variables market-to-book ratio to divide firms into portfolios (e.g., Barra, Fama & French and Russell use this approach). All of the indexes mentioned above are formulated as the return on a portfolio of stocks which have high (or low) values on the firm characteristics specified above. In tests of return-generating processes, researchers frequently use the difference in return between a portfolio with high values for some characteristics and a portfolio with low values for the same characteristics. The four-index model using the Pru-Bache indexes results in a smaller average absolute value of residual correlations (and average correlations) than do the four-index models using market-to-book ratios (The Barra and Russell indexes).[15] These differences are statistically significant using a simple *t* test and using stochastic dominance tests. Thus the Prudential Bache multi-criteria growth index performs better than one that classifies firms solely by their market-to-book ratios.

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two groups with respect to R.G.P.

[15] In each alternative four-index model, we use the difference between the returns on two portfolios as a fourth index. Barra separates the firms in the S&P 500 into two groups (growth and value) based on their market-to-book ratios. For the Russell growth-value index, we use the Russell 1000 value and growth indexes; these are constructed by splitting the largest 1,000 stocks into two groups by market-to-book ratios.

The reduction in covariance due to the introduction of a fifth index can be picking up an independent influence or the effect of common holdings. Only after we estimate this impact can we separate out the effect of a fifth index from the effect of common holdings.

C. Estimating the Effect of Common Holdings

As discussed earlier, although there are many advantages of using mutual fund data to explore return-generating processes, a disadvantage is that to the extent funds hold the same stocks, part of the correlation between funds will be due to common holdings. In this section we derive the relationship between the residual covariance between funds and the variance and covariance of the securities they hold. In the next section we use this relationship to analyze how much of the covariance captured by any index is due to common holdings and how much captures a common influence.[16]

Many mutual funds tend to hold the same stocks, and obviously the correlation between the parts of their holdings which are in common is perfect (equal to one). Unless factors in the return-generating process capture the returns on a portfolio of these common holdings, common holdings will explain part of the residual correlation between funds.

To examine the effect of common holdings, assume for the moment that the residual

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[16] There is another possible explanation. The MGO variable may be picking up some dynamic element of mutual fund trading. While this may be true, the failure of the momentum variable to add to performance suggests that the explanatory power that we pick up is not due to momentum trading as has been suggested.

variance for each stock i ($Var(e_i)$) is the same, i.e., $Var(e_i) = CVAR$ for all i, and that the residual covariance between each pair of stocks i and j ($Cov(e_ie_j)$) is the same, i.e., $Cov(e_ie_j) = CCOV$ for all i and j. Then the covariance of the residual returns between two funds A and B ($Cov(e_Ae_B)$) can be represented as:

$$Cov(e_A e_B) = \sum_{i \in S} X_{Ai} X_{Bi} CVAR + \sum_{i} \sum_{\substack{j \\ j \neq i}} X_{Ai} X_{Bj} CCOV \qquad (1)$$

where S is the set of stocks held in common and X_{Ai} represents the proportion invested in stock i by fund A.

Recognizing that the set notation can be dropped since $X_{Ai}\ X_{Bi} = 0$ for i not in S and rearranging equation (1) by combining summations and adding and subtracting $\sum_i X_{Ai} X_{Bi} CCOV$ yields:

$$Cov(e_A e_B) = \sum_{i} X_{Ai} X_{Bi} \left[CVAR - CCOV\right] + \sum_{i} \sum_{j} X_{Ai} X_{Bj} CCOV \qquad (2)$$

The first term in the right-hand side of equation (2) represents the marginal impact of common holdings on the residual covariance of a pair of funds. Now funds might not be 100 percent invested in common stocks. Equations (1) and (2) embody the assumption that all residual fund covariance comes from holding stocks.[17] We can scale equation (2) by the percentage of stock held by each fund:

[17] While this assumption is not strictly true, it should be a very good approximation. As shown in Blake, Elton and Gruber (1993), once the effect of a general bond return index is removed, correlations between the residuals of bond portfolios are small, and we have removed a bond index effect here. In addition, the variances of the residuals for bond portfolios after a bond index effect is removed are quite small relative to those for stock portfolios.

$$\frac{Cov(e_A e_B)}{\sum_i X_{Ai} \sum_j X_{Bj}} = CCOV + [CVAR - CCOV] \times \left[\frac{\sum_i X_{Ai} X_{Bi}}{\sum_i X_{Ai} \sum_j X_{Bj}} \right] \quad (3)$$

Equation (3) can then be estimated as a cross-sectional linear regression model:

$$\frac{Cov(e_A e_B)}{\sum_i X_{Ai} \sum_j X_{Bj}} = \gamma_0 + \gamma_1 \left[\frac{\sum_i X_{Ai} X_{Bi}}{\sum_i X_{Ai} \sum_j X_{Bj}} \right] + \eta_{AB} \quad (4)$$

where η_{AB} is a random error term.

Estimates of the common residual covariance between stocks (*CCOV*) and the stocks' common residual variance (*CVAR*) from any model can be computed directly from the regression estimates of γ_0 and γ_1 in equation (4).

The above analysis assumes that the residual covariance between each pair of stocks is the same and that the residual variance of all stocks is the same. However, we might expect the residual variance and covariance for stocks held by aggressive growth funds to be different from the residual variance and covariance for stocks held by income funds. We divided our sample funds into three types—aggressive growth (AG), growth (G), and income (I)—and use equation (4) to estimate stock residual risk and covariance for each of the types of funds.

To estimate equation (4) we need to know the composition of the portfolio of each fund to which it is fit. Because of the difficulty of obtaining composition data, we obtained data only as of one date, December 1992, and for the funds in only one of our subsamples (group A). We lost 11 firms from sample A because of data problems and renamed the reconstituted group "Group D."[18]

Before we turn to our analysis using equation (4), let us examine the amounts of common holdings in group D. Table 4 shows the distribution of common holdings within and between types of funds with different policies. The median common holdings range from 1.3% to 5.6%, depending on the sample[19]. For four of the samples, the 75th percentile is greater than 5%. This is substantial, given the residual correlations we are observing.

Table 5, for our base four model and each of the five-index models, shows the estimates of residual covariances and variances of individual securities for each fund type and across fund types obtained from the regression employing equation (4). The estimates are consistent with what we expect to find.[20] The estimated residual variance is highest for the stocks held by aggressive growth funds, next highest for stocks held by growth

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[18] To the extent that the percentages of stocks held in common on this date were not representative of the whole of our sample period, this should bias the results against finding that common holdings help explain the covariance between funds. The source of our composition data was Morningstar. Group A contained 89 firms. Eleven of these firms were eliminated because we could not obtain composition data, or because their investment policy was outside the three groups described above, or because the data on fund composition contained inconsistencies or was incomplete.

[19] The percentage of common holdings shown in Table 4 is obtained by taking the square root of the last term in brackets in equation (3).

[20] As a check on the regression estimate, we examined equation (3) only for those few funds which had common holdings close to zero. For those funds, within any fund type or pair of fund types, the average scaled residual covariance between the funds should be equal to the residual covariance between stocks held by the funds. The results from this procedure produced estimates of residual covariances consistent with those obtained from the regression procedure described above. For example, for the four-index model the estimate from pairs of funds of type AG was .6464 for the regression and .5547 for zero holdings; for pairs of types AG and G it was .2535 for the regression and .2676 for zero holdings; for pairs of types AG and I it was .1196 for the regression and .1277 for

funds and much lower for stocks held by income funds. The residual variances of stocks held by two different types of funds show a similar pattern, e.g., the stocks held by other aggressive growth and growth funds having a higher residual variance than those stocks held by other pairs of funds. This ordering of the residual variance is consistent with what we would expect on the basis of the fund's stated policy. The covariances estimated in Table 5 also fit a reasonable pattern. For example, the highest covariance is found between stocks held by aggressive growth funds.

D. Is It Common Holdings or a Systematic Factor?

In this section we examine how much of the reduction in residual covariance between funds caused by the introduction of a fifth factor is due to common holdings and how much is due to measuring a common influence.

From the mathematics of orthogonal multi-index models, the residual covariance between two funds *A* and *B* due to any index is:

$$\beta_{A,\,\mathrm{MGO}}\,\beta_{B,\,\mathrm{MGO}}\,Var(\mathrm{MGO}) \tag{5}$$

We can obtain an indication of the importance of common holdings by correlating the residual covariance explained by the fifth factor for each pair of funds (equation (5)) against the amount of residual covariance explained by common holdings. If the fifth factor was only capturing the impact of common holdings, the correlation should be one. The amount of residual covariance explained by common holdings is calculated by using

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zero holdings. This consistency gives us additional confidence in the regression estimates.

the first term on the right-hand side of equation (2) along with the estimates of variance and covariance of security residuals for the four-index case contained in Table 5. The R^2 is .22 for MGO, .11 for momentum, and .03 for sentiment.

Each of the candidates for a fifth index may come in, in part, because it picks up the effect of common holdings. An examination of the residuals from the four- and five-index models can give us a more precise estimate of how much of the reduction in covariance due to the introduction of the fifth index is due to common holdings and how much is due to capturing independent information.

When we introduce a fifth index and estimate the variance and covariance between the residual risk for individual securities (Table 5), an interesting pattern emerges. First, consider the estimated covariance from Panel A of Table 5. When MGO is introduced there is a dramatic reduction in estimated covariance between residuals for securities versus the base four model. Four of the six estimated covariances are not significantly differ from zero. The two that are significant have opposite signs, and the average magnitude is reduced by two-thirds. Since it is the presence of covariance between securities that indicates additional factors, this supports the conclusion that the addition of MGO captures significant independent information. When sentiment or momentum is added to the base model, there is little effect on the estimated residual covariance and all covariance terms are still positively significantly different from zero. Thus momentum and sentiment capture little of the common movement between securities not explained by the base four model.

Now consider the variance term. As we showed earlier, the effect of common holding is contained in the estimate of the variance of the residuals between securities. If an index were proxying in part for common holding, it should reduce the estimate of the variances presented in Table 5, Panel B. When sentiment is introduced as the fifth index, there is almost no reduction in the variance of the residuals. When either MGO or momentum is introduced, there is a large decrease in the variance estimate, indicating that both of the indexes pick up in part the influence of common holdings.

Examining the impact of candidates for the fifth index on the correlation between funds, we see that MGO has a large impact because it explains a large part of the covariance between stocks not picked up by the four-index model, and picks up part of the impact of common holdings. The momentum index has no role in explaining the covariance between stocks, but it might have some impact on the covariance between funds because it captures some of the influence of common holdings. The sentiment index has no effect on fund covariances because it neither explains security covariances nor is associated with common holdings.

A second way to examine how much of the reduction in covariance between mutual funds due to the introduction of a fifth index is due to common holdings and how much is capturing independent information is to directly examine the distribution of the correlation coefficients between funds. In Table 6 we present the distribution of absolute values of residual correlation coefficients for different return-generating processes with and without making the adjustment for common holdings.[21] Let's start by examining the residual correlation distribution from the four-index model shown in Panel A of Table 6. Adjusting for common holdings lowers the average absolute value correlation from .130 to .119. Not only is the difference statistically significant, but the adjustment shows stochastic dominance across the cells in the table. Common holdings have a major impact on reducing the absolute values of correlations of residuals from the four-index model.

When we examine the residual correlation distribution from a model using MGO as the fifth index without any adjustment for common holdings (shown in the column labeled "MGO" in Panel B of Table 6), we find that the average absolute value of the residual correlations is reduced below that found for the four-index model with adjustment for common holdings. The results are statistically significant at the .01 level and show stochastic dominance. Clearly, then, the MGO index introduces information not captured by common holdings. Examining the column labeled "adjusted" in Panel A of Table 6, we see that employing the correction for common holdings reduces the absolute correlation between residuals. While the difference is statistically significant, the

[21] Similar results to those obtained for MGO are found when the fifth index is constructed from a one-factor analysis of the residuals from the four-index model. In this case the R^2 is .13 rather than .22. The effect of common holdings is estimated by using the first term in the right-hand side of equation (2) along with estimates of residual variance and covariance of securities from Panel B of Table 5 and the percentages of stocks in common. This estimate of the funds' residual covariance due to common holdings is subtracted from the funds' actual residual covariance to adjust for the effect of common holdings.

distribution does not show stochastic dominance. However, using the correction for common holdings reduces the largest absolute values of residual correlations.

When we examine a model using sentiment as the fifth index, we find results almost identical to those found for the base model. The fact that both the unadjusted and adjusted distribution of the correlation coefficients of the residuals are virtually the same as the base four model indicates that sentiment picks up neither a common influence nor common holdings. When we examine the five-index model containing momentum, we see that the use of this index decreases the absolute correlation of residuals below the level of the four-index model (though they are above the level found for the five-index model containing MGO). However, after the adjustment for common holdings is made, the performance of the sentiment model is almost exactly equivalent to the four-index model. The apparent superiority of the momentum index was due to its ability to capture common holdings.

These results are consistent with the results presented earlier in this section. Adding a sentiment index to the four-index model adds nothing to performance since the index captures neither a common influence of stock returns nor common holdings. Adding a momentum index helps explain the correlation of fund returns, but only because it captures common holdings. Adding the MGO index results in a large improvement, partially because it captures a new systematic influence and partially because it captures common holdings.

E. Is the Addition of MGO Enough?

In this section we present evidence which suggests that our five-factor fundamental model with MGO is a sufficient description of the return-generating process. Our evidence consists of three parts: 1) an examination of cross-sectional estimates of the covariance between securities; 2) an examination of how much of the remaining covariance between funds is due to common holdings; and 3) a comparison of the fundamental model with multi-index models based on factor analysis.

Covariance between common stock residuals comes about because of randomness and because of omitted factors. If the model captured all common influences, then the covariances of the residuals between stocks would average zero, covariances between stock residuals due to randomness would tend to cancel out in a portfolio, and the only reason funds would have a residual covariance would be common holdings. When we examine Table 5 for MGO, all estimates of the residual covariance estimates between securities for the five-index model are not statistically different from zero except for two cases: the aggressive growth and the aggressive growth and income samples. In these two cases they are significant, but with opposite signs. This is a strong indication that five indexes capture all common influences.

Another way to look at the data in Table 5 is to ask how much of the forecasted residual covariance is due to common holdings and how much is due to any remaining covariance between individual securities. With the five-index model with MGO, on average the proportion of the forecasted residual covariance due to common holdings is 60 times that due to the residual covariance between securities. For the group with the largest estimate for the residual covariance between securities, aggressive growth with other aggressive growth, the proportion of the estimated residual covariance due to common holdings is 80%. This is strong evidence that five indexes are enough to capture common influences.

A final way to examine if we have captured the important common factors is to compare our results with those from a purely statistical extraction of factors. We performed a maximum-likelihood factor analysis on the variance-covariance matrix of the funds' excess returns for each of our three samples. We extracted one to eight factors. If these are truly common, then the factors extracted from one sample should explain the structure of returns for a different sample. Thus sample A factors were used as indexes in a model for sample B, sample B for C and C for A. While the average absolute correlation decreases as we add more indexes, the decrease becomes much smaller as we move from four to five to six indexes and some samples cease to exhibit stochastic dominance as we go from four to five indexes. The evidence is consistent with the presence of four, or possibly five, statistical factors.

The average absolute value residual correlation from our five-factor prespecified model (base plus MGO) is the same or less than that of the four-factor model from the factor analysis.[22] Furthermore, when we regress each of the four factors from the statistical factor model on the five prespecified factors, the four statistical factors are highly related to our five prespecified factors. For example, the average correlations are 1.00, .89, .76 and .58 for Group A.[23] In addition, all of the five prespecified factors are significantly related to the statistical factors at the .01 level. Since four statistical factors capture the bulk of the residual covariances between funds, and since our five prespecified indexes perform as well or better, the five prespecified indexes seem to capture all common influences.

In this section we have presented evidence that four factors (or at most five) derived from maximum-likelihood factor analysis seem to capture the covariance between securities. In addition, our five-index fundamental model (base plus MGO) does at least as good a job of explaining covariances as does the four-index factor model. The performance is close, which is not surprising since each of the four factors is highly correlated with the five indexes in our fundamental model. When the base plus MGO five-index model is used, the estimate of the residual covariance between securities for most groups is not statistically significantly different from zero, and almost all of the estimated residual covariance between funds comes from common holdings.

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[22] The comparison is biased in favor of the statistical model because we fit and test the model in the same time period.

[23] The same results hold if we reverse the process. Each of the five fundamental factors is highly related to the four statistical factors.

III. TEST ON PASSIVE PORTFOLIOS

As discussed earlier, there are some disadvantages of using mutual funds to test R.G.P. First, there is a possibility that some of the factors simply capture dynamic trading strategies such as herding or momentum. Second, factors could be present simply because they capture the effect of common holdings. Passive portfolios of individual securities can serve as a holdout sample and serve as a convenient population to examine these concerns.

We formed passive portfolios based on size and industry. These classifications were used because of their wide use in testing asset pricing models and R.G.P.'s (see Fama, French (1996) and Gibbons, Ross & Shanken (1989)). For size portfolios we used the ten CRSP size deciles. The industry portfolios were constructed by selecting a random sample of 483 stocks from the CRSP tape and then dividing this sample into 28 portfolios by using two digit SIC codes. In Table 7 we present the distribution of the absolute residual correlations for our base four-index model and four five-index models for both the ten size portfolios and the industry portfolios. In Table 8 we present the percentages of statistically significant regression coefficients for the same portfolios and models.

First consider Table 7. In both samples (industry portfolios and size portfolios), adding either a sentiment index or a momentum index to the base four model does not lead to a decrease in the average absolute correlation coefficient. In fact, in each case the average absolute correlation is higher except for a tie when we add momentum to the industry portfolios. Clearly this criteria does not support using either sentiment or momentum as a fifth index.

When we examine the two candidates for the fifth index that were developed from mutual fund data, factor and MGO, we find a large improvement in results compared to the four-index model. Adding either the factor index or the mutual fund growth index results in a decrease in the average correlation coefficient and in the average absolute correlation coefficient, and both models exhibit distributions of the absolute correlation coefficient which dominate the distribution for the four-index model. Furthermore, performing a *t* test on the pairwise differences in absolute correlation coefficients shows that both models outperform the four-index model at the 5% level of significance. These results hold for both the industry sample and the size sample.

We see analogous results when we examine the percentages of betas on each index that are significantly different from zero. In the industry sample (Panel A of Table 8) the sentiment index is significant 7.14% of the time. We would expect it to be significant 5% of the time at the .05 level of significance being used. Similarly, momentum is only significant 17.86% of the time. While this is more than expected by chance, it is only significant half a many times as MGO or the factor model. The factor index is significant 42.9% of the time and the mutual fund index is significant 35.7% of the time, much higher values than we would expect on the basis of chance. The results for the size sample (Panel B) are even stronger. The sentiment index is never significant. While the beta on momentum is significant 20% of the time, the factor and MGO betas are significant 90% of the time. There may be some information in the momentum index though it is not nearly as strong an influence as either the MGO or factor index.

The two-indexes developed using mutual fund data have applicability well beyond the study of mutual funds, and there is little support for sentiment or momentum.

V. CONCLUSION

In this paper we have examined several alternative models of the return-generating process. We have chosen to test the models on mutual fund data because these data lead to a natural differentiation on important influences while damping out random influences. The research reveals that:

1. A four-index model based on widely available indexes of securities with different characteristics explains a great deal of the correlation between mutual funds. All of the four indexes have been used in some form in previous papers, although the particular form we use has not previously been tested against alternative specifications.
2. A value-growth index based on firm fundamentals is better in explaining covariance than an index based on market-to-book values.
3. Using factor analysis, there is very strong evidence that after removing the four indexes a fifth index (a factor constructed from the residuals) has strong explanatory

power. This is true whether the importance of the fifth index is judged by examining the number of significant betas or by examining its ability to explain the correlation of the residuals from a four-index model.

4. A fifth index representing an equally weighted portfolio of mutual funds with growth as a stated objective performs almost identically with the factor index mentioned above. This is due in part to the fact that the correlation between the two models is extremely high. It also means that we can identify the fifth factor.
5. Some of the residual correlation between mutual funds is due to common holdings. We have presented a methodology for removing this influence. This in itself is important for studying the effect of forming portfolios of mutual funds.
6. We find that part of the performance of our fifth index (whether formed by factor analysis or a portfolio of growth mutual funds) is accounted for by common holdings, but part is due to capturing a unique influence.
7. When we examine either sentiment or momentum as a fifth index, the results are different. There is no support for sentiment. Momentum does pick up part of the covariance among funds, but its importance is primarily due to it capturing the impact of common holdings.
8. Finally, we test our five-index model on passive portfolios of common stocks. This serves several purposes. It allows us to test the performance of the fifth index where its importance is not obfuscated by common holdings. It acts as a holdout sample. It

allows us to test the fifth index on a sample where the results cannot be caused by some element of active management. It allows us to see if the influences studied earlier in the paper have significance for common stock returns. The results show that MGO is important. The passive portfolios provide no support for sentiment, and using momentum does not result in a reduction in the covariance between residuals.

TABLE 1

COMPARISON OF ALTERNATIVE RETURN-GENERATING PROCESSES

	One-Index Model			Base Four-Index Model			Factor		
Threshold Value	A	B	C	A	B	C	A	B	C
0.010	3818	3827	3812	3720	3705	3707	3690	3676	3665
0.025	3665	3681	3653	3406	3419	3400	3339	3302	3292
0.050	3394	3432	3394	2902	2948	2887	2741	2687	2744
0.100	2872	2983	2908	1996	2034	2075	1767	1700	1749
0.150	2348	2545	2388	1279	1285	1318	1052	979	948
0.200	1915	2141	2008	812	765	802	529	507	475
0.250	1528	1748	1630	454	404	455	261	235	217
Average Abs. Val. Correlation	0.228	0.244	0.235	0.125	0.123	0.126	0.107	0.104	0.103
Average Correlation	0.193	0.218	0.213	0.065	0.078	0.082	0.023	0.026	0.003

	Sentiment			Momentum			MGO		
Threshold Value	A	B	C	A	B	C	A	B	C
0.010	3719	3732	3701	3682	3703	3681	3676	3680	3672
0.025	3406	3433	3384	3403	3387	3316	3300	3293	3333
0.050	2909	2961	2914	2875	2894	2815	2771	2682	2746
0.100	1995	2026	2079	1947	1962	1917	1750	1682	1734
0.150	1271	1286	1311	1237	1214	1195	1033	967	960
0.200	804	765	799	715	689	682	540	493	488
0.250	455	398	460	396	350	375	262	243	225
Average Abs. Val. Correlation	0.125	0.123	0.126	0.120	0.118	0.117	0.107	0.103	0.104
Average Correlation	0.065	0.078	0.081	0.055	0.068	0.067	0.014	0.017	0.019

This table shows number of absolute values of pairwise residual correlations greater than threshold values for groups A, B and C (@ 89 funds).
The one-index model uses the excess return (over 30-day T-bill rate) on the S&P 500 index.
The base four-index model uses the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes.
The remaining models are five-index models using the base four-index model plus an additional index as follows:
"Factor" uses a single factor extracted from the residuals of the sample funds' excess returns regressed on the base four-index model, where group A uses a factor extracted from group C, group B uses a factor from group A, and group C uses a factor from group B;
"Sentiment" uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model;
"Momentum" uses Carhart's "momentum" factor-mimicking portfolio, orthogonalized to the base four-index model;
"MGO" uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base 4-index model.

TABLE 2

PERCENTAGE OF REGRESSION COEFFICIENTS SIGNIFICANT AT THE 5% LEVEL (267 FUNDS)

Model	S&P 500	Small-Large	Growth-Value	Bond	Fifth Index
Base	100.00%	87.27%	73.78%	46.82%	
Factor	100.00%	88.01%	75.28%	49.44%	71.54%
MGO	100.00%	87.64%	74.91%	49.06%	71.54%
Momentum	100.00%	87.64%	74.91%	47.19%	48.31%
Sentiment	100.00%	87.27%	73.78%	46.44%	9.36%

This table shows the percentage of regression coefficients that are different from zero at 5% level for 267 funds when a time-series regression is run on the returns for each fund against the variables identified in the body of the table.
The base model is a four-index model using the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes. The alternative five-index models use the base four-index model plus an additional index as follows:
"Factor" uses a single factor extracted from the residuals of the sample funds' excess returns regressed on the base four-index model, where group A uses a factor extracted from group C, group B uses a factor from group A, and group C uses a factor from group B;
"Sentiment" uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model;
"Momentum" uses the Carhart's factor-mimicking portfolio for one-year momentum in stock returns, orthogonalized to the base 4-index model;
"MGO" uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base 4-index model.

TABLE 3

DISTRIBUTION OF BETAS FROM ALTERNATIVE MODELS

PANEL A: 267 FUNDS

	Base 4-Index Model				Alternative 5th Index		
index	S&P 500	Small-Large	Growth-Value	Bond	Sentiment	Momentum	MGO
20th percentile	0.685	0.094	-0.096	0.017	-0.025	0.001	0.215
median	0.836	0.231	0.152	0.103	0.032	0.066	0.592
80th percentile	0.936	0.392	0.480	0.221	0.104	0.154	1.081
standard deviation	0.173	0.201	0.346	0.172	0.087	0.103	0.526

PANEL B: CRSP DECILES

	Base 4-Index Model				Alternative 5th Index		
index	S&P 500	Small-Large	Growth-Value	Bond	Sentiment	Momentum	MGO
20th percentile	0.931	0.253	-0.327	-0.057	-0.024	-0.040	0.042
median	0.961	0.711	-0.082	0.041	-0.009	0.022	0.714
80th percentile	0.973	0.999	-0.041	0.118	0.035	0.053	0.866
standard deviation	0.022	0.423	0.170	0.074	0.031	0.117	0.382

The indexes are as follows:
"S&P 500" is the excess return (over the 30-day T-bill rate) of the S&P 500 index; "Small-Large" is the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes; "Growth-Value" is the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes; "Bond" is the excess return of a composite bond index; "Sentiment" is the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model; "Momentum" is Carhart's factor-mimicking portfolio for one-year momentum in stock returns, orthogonalized to the base 4-index model; "MGO" is the the excess return of the Morningstar Growth fund index, orthogonalized to the base 4-index r

TABLE 4

DISTRIBUTION OF PERCENTAGES OF COMMON HOLDINGS

Fund Types	proportion with 0%	median %	25th percentile	75th percentile	highest %
AG, AG	8.89%	2.85%	1.88%	5.28%	8.17%
G, G	5.71%	4.57%	3.13%	6.22%	12.02%
I, I	0.57%	5.59%	3.95%	6.73%	11.44%
AG, G	17.71%	2.71%	1.13%	4.53%	10.53%
AG, I	33.03%	1.34%	0.00%	2.99%	6.64%
G, I	4.24%	4.25%	2.89%	5.75%	16.12%

"AG" = aggressive growth funds; "G" = long-term growth funds; "I" = income, balanced, and growth and income funds.
The percentages shown are obtained from Morningstar composition data for group D (78 funds from group A).
For the last four columns, the percentages shown are based on the square root of the sum of the scaled products of the fractions of securities held in common between pairs of funds (i.e., the square root of the last term in equation (3) in the text).

TABLE 5

ESTIMATES OF VARIANCES AND COVARIANCES OF RESIDUALS FOR INDIVIDUAL SECURITIES FROM EQUATION 4

Fund Types	Panel A: Estimated Covariance				Panel B: Estimated Variance			
	Base	Sentiment	Momentum	MGO	Base	Sentiment	Momentum	MGO
AG, AG	0.6464 *	0.6059 *	0.6509 *	0.3199 *	159.42 *	150.60 *	104.47	58.58
G, G	0.1160 *	0.1105 *	0.1043 *	-0.0614	100.10 *	100.15 *	72.39 *	35.37 *
I, I	0.1343 *	0.1326 *	0.1164 *	0.0003	11.63	11.85	8.86	24.91 *
AG, G	0.2535 *	0.2375 *	0.2296 *	-0.0332	176.38 *	174.53 *	126.39 *	79.37 *
AG, I	0.1196 *	0.1126 *	0.0880 *	-0.0991 *	91.49 *	88.34 *	53.59	90.26 *
G, I	0.1843 *	0.1804 *	0.1444 *	-0.0322	13.48	13.98	8.66	29.31 *

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* = significant at the 5% level. (For estimated variance, the significance refers to the slope coefficient of equation 4; the estimated variance is obtained by adding the intercept to the slope.)

For fund types, "AG" = aggressive growth funds, "G" = long-term growth funds, and "I" = income, balanced, and growth and income funds.
The base four-index model uses the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes.
The "Sentiment" five-idex model uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model.
The "Momentum" five-index model uses Carhart's "momentum" factor-mimicking portfolio, orthogonalized to the base four-index model.
The "MGO" five-index model uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base 4-index model.

TABLE 6

THE EFFECT OF COMMON HOLDINGS

Threshold Value	Base	Adjusted Base	Sentiment	Adjusted Sentiment
0.010	2858	2853	2859	2846
0.025	2614	2589	2617	2592
0.050	2254	2186	2259	2184
0.100	1590	1475	1593	1478
0.150	1076	942	1071	942
0.200	692	549	687	545
0.250	391	288	392	300
Average Abs. Val. Correlation	0.130	0.119	0.130	0.119
Average Correlation	0.079	0.047	0.0777	0.0455

Threshold Value	Momentum	Adjusted Momentum	MGO	Adjusted MGO
0.010	2829	2834	2806	2808
0.025	2614	2580	2522	2551
0.050	2211	2163	2133	2140
0.100	1542	1449	1379	1361
0.150	1015	902	833	822
0.200	598	507	444	414
0.250	329	262	218	199
Average Abs. Val. Correlation	0.123	0.115	0.110	0.108
Average Correlation	0.066	0.042	0.017	-0.013

This table shows the number of absolute values of pairwise residual correlations greater than threshold values for group D (78 funds from group A).
"Adjusted" means that the funds' residual covariances were adjusted for the effect of common holdings before calculating correlations.
The base four-index model uses the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes.
The "Sentiment" five-idex model uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model.
The "Momentum" five-index model uses Carhart's "momentum" factor-mimicking portfolio, orthogonalized to the base four-index model.
The "MGO" five-index model uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base 4-index model.

TABLE 7

COMPARISON OF FOUR-INDEX BASE MODEL AND ALTERNATIVE FIVE-INDEX MODELS FOR SIC GROUPS

Threshold Value	Base	Factor	Sentiment	Momentum	MGO
0.010	360	354	360	359	360
0.025	331	327	329	327	329
0.050	285	277	283	283	279
0.100	205	198	206	204	198
0.150	137	136	141	136	133
0.200	88	83	87	85	84
0.250	40	37	41	41	36
Average Abs. Val. Correlation	0.131	0.128	0.132	0.131	0.128
Average Correlation	0.055	0.044	0.055	0.056	0.045

COMPARISON OF FOUR-INDEX BASE MODEL AND ALTERNATIVE FIVE-INDEX MODELS FOR CRSP DECILES

Threshold Value	Base	Factor	Sentiment	Momentum	MGO
0.010	45	45	45	45	44
0.025	43	42	42	45	43
0.050	42	41	42	42	39
0.100	37	37	37	37	37
0.150	36	34	36	36	34
0.200	34	29	34	35	28
0.250	30	25	30	30	23
Average Abs. Val. Correlation	0.341	0.274	0.342	0.346	0.272
Average Correlation	0.255	0.194	0.256	0.263	0.212

This table shows the number of absolute values of pairwise residual correlations greater than threshold values for two samples: 28 stock portfolios, where each portfolio is an equally weighted portfolio of stocks grouped by two-digit SIC codes, and ten size portfolios, represented by the CRSP size deciles.

The base four-index model uses the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes. The alternative five-index models use the base four-index model plus an additional index as follows:
"Factor" uses a single factor extracted from the residuals of the funds in group A, where the residuals were obtained by regressing the excess returns of the funds in group A on the base four-index model;
"Sentiment" uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model;
"Momentum" uses Carhart's "momentum" factor-mimicking portfolio, orthogonalized to the base four-index model;
"MGO" uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base four-index model.

TABLE 8

PERCENTAGE OF REGRESSION COEFFICIENTS SIGNIFICANT AT THE 5% LEVEL (28 SIC PORTFOLIOS OF STOCKS)

Model	S&P 500	Small-Large	Growth-Value	Bond	Fifth Index
Base	100.00%	92.86%	28.57%	32.14%	
Factor	100.00%	92.86%	28.57%	32.14%	42.86%
Sentiment	100.00%	92.86%	28.57%	28.57%	7.14%
Momentum	100.00%	92.86%	28.57%	32.14%	17.86%
MGO	100.00%	92.86%	28.57%	32.14%	35.71%

PERCENTAGE OF REGRESSION COEFFICIENTS SIGNIFICANT AT THE 5% LEVEL (CRSP SIZE DECILES)

Model	S&P 500	Small-Large	Growth-Value	Bond	Fifth Index
Base	100.00%	100.00%	50.00%	20.00%	
Factor	100.00%	100.00%	60.00%	30.00%	90.00%
Sentiment	100.00%	100.00%	50.00%	20.00%	0.00%
Momentum	100.00%	100.00%	50.00%	20.00%	20.00%
MGO	100.00%	100.00%	70.00%	20.00%	90.00%

This table shows percentage of regression coefficients that are different from zero at the 5% level
when a time-series regression is run on the returns for each portfolio against the variables identified in the body of the table.
The base model is four-index model using the excess return of the S&P 500 index, the excess return of a composite bond index, the average of the Pru-Bache small-cap indexes minus the average of the Pru-Bache large-cap indexes, and the average of the Pru-Bache growth indexes minus the average of the Pru-Bache value indexes. The alternative five-index models use the base four-index model plus an additional index as follows:
"Factor" uses a single factor extracted from the residuals of the funds in group A, where the residuals were obtained by regressing the excess returns of the funds in group A on the base four-index model;
"Sentiment" uses the change in the discount of a value-weighted portfolio of closed-end funds, orthogonalized to the base four-index model;
"Momentum" uses Carhart's "momentum" factor-mimicking portfolio, orthogonalized to the base four-index model;
"MGO" uses the the excess return of the Morningstar Growth fund index, orthogonalized to the base four-index model.

model.

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