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DOES MUTUAL FUND PERFORMANCE VARY OVER THE BUSINESS CYCLE?

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Comments welcome.

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Abstract

Conditional factor models allow both risk loadings and performance over a period to be a function of information available at the start of the period. Much of the literature to date has allowed risk loadings to be time-varying while imposing the assumption that conditional performance is constant. We develop a new methodology that allows conditional performance to be a function of information available at the start of the period. This methodology uses the Euler equation restriction that comes out of the factor model rather than the beta pricing formula itself. The Euler equation restrictions that we develop can be estimated using GMM. It is also possible to allow the factor returns to have longer data series than the mutual fund series as in Stambaugh (1997). We use our method to assess the conditional performance of funds in the Elton, Gruber and Blake (1996) mutual fund data set. Using dividend yield to track the business cycle, we find that conditional mutual fund performance moves with the business cycle, with all fund types except growth performing better in downturns than in peaks. The converse holds for growth funds, which do better in peaks than in downturns.

1 Introduction

Mutual fund performance has long been of interest to financial economists, both because of its implications for market efficiency, and because of its implications for investors. A key question in evaluating performance is the choice of the benchmark model. Without a model for normal returns, it is impossible to define a mutual fund return as abnormal. Recently, the asset pricing literature has emphasized the distinction between unconditional and conditional asset pricing models. The relative success of conditional models raises important questions for the mutual fund researcher. How does one evaluate performance when the underlying model is conditional? Might performance itself be conditional? In principle, a conditional model allows both risk loadings and performance over a period to be a function of information available at the start of the period. Much of the literature to date has allowed risk loadings to be time-varying while imposing the assumption that conditional performance is a constant. For example, Ferson and Schadt (1996), an early contribution to the literature on conditional performance, makes exactly this assumption.

We develop a new methodology that allows conditional performance to be a function of information available at the start of the period. This methodology uses the Euler equation restriction that comes out of a factor model rather than the beta pricing formula itself. While the Euler equation does not provide direct information about the nature of time variation in the risk loadings, it can provide direct information about time variation in conditional performance. In contrast, the classic time-series regression methodology can provide direct information about time-varying betas (see Ferson and Schadt, 1996) but not about time-varying performance.

A set of factors constitute a conditional beta-pricing model if the conditional expected return on any asset is linear in the return's conditional betas with respect to the factors. It is well known (see Cochrane, 2001) that a set of factors constitutes a conditional beta-pricing model if and only if there exists a linear function of the factors (where the coefficients are in the conditional information set) that can be used as a stochastic discount factor in the conditional Euler equation. Our methodology determines the parameters of this stochastic discount factor by correctly pricing the factor returns. This estimated stochastic discount factor is then used to calculate the conditional performance of a fund by replacing the fund's return in the Euler equation with the fund return in excess of its conditional performance. We allow the parameters of the stochastic discount factor to be linear in the information variables, as in Lettau and Ludvigson (2001b), and we use the same linear specification for conditional fund performance. However, the methodology is sufficiently flexible to allow arbitrary functional forms for both.

The Euler equation restrictions that we develop can be estimated using GMM. It is also possible to allow the factor returns to have longer data series than the mutual fund series as in Stambaugh (1997). A number of recent Bayesian mutual fund papers have taken advantage of the availability of longer data series for the factor returns than the mutual fund returns (see Pastor and Stambaugh, 2002a and 2002b). We will extend their methods to a frequentist setting.

We use our method to assess the conditional performance of funds in the Elton, Gruber and Blake (1996) mutual fund data set. Conditional performance is estimated fund by fund and also for equal-weighted portfolios grouped by fund type. Three of the four fund types are the Weisenberger categories, maximum capital gain, growth, and growth and income, while the fourth group includes all other funds in our sample. We use the dividend yield as the information variable because it has been found to predict stock returns and move with the business cycle (see Fama and French, 1989). We estimate three different factor models: the CAPM whose only factor is the excess return on the value-weighted stock market; the Fama and French (1993) model whose three factors are the market excess return, the return on a portfolio long high and short low book-to-market stocks, and the return on a portfolio long big stocks and short big stocks; and the four factor model of Carhart (1997) whose factors are the three Fama-French factors plus the return on a portfolio long stocks that performed well the previous year and short stocks that performed poorly. Three versions of each model are estimated. The first is the usual unconditional model. The second is the conditional model with performance not allowed to depend on the information variable, as in Ferson and Schadt (1996). The third is the conditional model with performance that is allowed to vary with the information variable. Implementing this last version is the innovation of the paper.

We find that conditional mutual fund performance moves with the dividend yield. In particular, a Wald test for equality to zero of the performance coefficients on dividend yield for the four fund types is always rejected, irrespective of the pricing model being used as the benchmark. For the maximum capital gain group, this coefficient is significantly positive when performance is measured relative to the CAPM. For the growth group, this coefficient is significantly negative when performance is measured relative to the Fama-French 3-factor model or the Carhart 4-factor model. Moreover, we find that for all fund types except growth, abnormal performance rises during downturns, regardless of which factor model is used. For growth funds, abnormal performance rises during peaks. The clear implication of our findings is that fund performance varies over the business cycle.

The two papers closest to ours are Ferson and Harvey (1999) and Kosowski (2001). Ferson and Harvey extend the times-series regression approach in Ferson and Schadt (1996) to allow for time-varying conditional performance. However, their interpretation of the regression coefficients is highly sensitive to their assumption that the conditional betas are linear in the information variables. Under a different but still plausible structure on the conditional model this coefficient can be non-zero even with zero abnormal performance. Kosowski (2001) uses a regime-switching model to assess time-variation in mutual fund performance. His regimes are fund-specific, so it difficult to interpret his findings as evidence for business-cycle variation.

The paper is organized as follows. Section 2 describes the theory and the empirical methodology while Section 3 discusses the data. Section 4 presents the results and Section 5 concludes.

2 Methodology

This section discusses the theory and methodology behind our conditional performance measure. Section 2.1 describes the benchmark model for asset returns. Performance is measured relative to this model. Section 2.2 defines our measure of conditional abnormal performance and discusses the estimation. Section 2.3 compares our measure to others in the literature.

2.1 Benchmark Model

We start by assuming a conditional beta pricing model of the form

$$E_t[r_{t+1}] = E_t[\mathbf{r}_{\mathbf{p},t+1}]^\top \boldsymbol{\beta}_{t+1}, \tag{1}$$

where $\boldsymbol{\beta}_t$ is a column vector equal to

$$\boldsymbol{\beta}_t = \mathrm{Var}_t(\mathbf{r}_{\mathbf{p},t+1})^{-1}\mathrm{Cov}_t(\mathbf{r}_{\mathbf{p},t+1}, r_{t+1}),$$

and $\mathbf{r}_{\mathbf{p},t+1}$ is a column vector of returns on zero-cost benchmark portfolios. In what follows, we will denote excess returns using lower-case r; gross returns will be denoted R. In the case where $\mathbf{r}_\mathbf{p}$ is the return on the market in excess of the riskfree rate, (1) is a conditional CAPM. When there are multiple returns, (1) can be interpreted as an ICAPM, or as a factor model where the factors are returns on portfolios.

As is well-known, (1) is equivalent to specifying a stochastic discount factor model which is linear in $\mathbf{r}_\mathbf{p}$, where the coefficients are time-varying. Following Cochrane (2001), we make the further assumption that the coefficients are linear functions of a state variable Z_t, which summarizes the information available to the investor at time t.[1]

Our stochastic discount factor is given by:

$$M_{t+1} = a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}. \tag{2}$$

For any return R that is correctly priced by M_{t+1},

$$E_t[R_{t+1}M_{t+1}] = 1. \tag{3}$$

Let R^f_{t+1} denote the riskfree rate of return. Because R^f_{t+1} is known at time t:

$$E_t[M_{t+1}] = \frac{1}{R_{f,t+1}}.$$

Zero-cost portfolios, or returns in excess of the riskfree rate satisfy:

$$E_t[r_{t+1}M_{t+1}] = 0. \tag{4}$$

Suppose that an asset with excess return r_{t+1} is priced correctly by M_{t+1}. Then (4) implies

$$\mathrm{Cov}_t\left(a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}, r_{t+1}\right) + E_t[M_{t+1}]E_t[r_{t+1}] = 0.$$

Because Z_t is known at time t,

$$E_t[r_{t+1}] = -\frac{(\mathbf{c} + \mathbf{d}Z_t)}{E_t[M_{t+1}]}^\top \mathrm{Cov}_t(\mathbf{r}_{\mathbf{p},t+1}, r_{t+1}). \tag{5}$$

Because M_{t+1} must price the reference assets correctly, (5) holds for the reference assets, and

$$\frac{(\mathbf{c} + \mathbf{d}Z_t)}{E_t[M_{t+1}]}^\top = -E_t[\mathbf{r}_{\mathbf{p},t+1}]^\top \mathrm{Var}_t(\mathbf{r}_{\mathbf{p},t+1})^{-1}. \tag{6}$$

Substituting (6) in to (5) produces (1). Thus specifying the stochastic discount factor as (2) implies a conditional beta pricing model.

2.2 Conditional Performance Measure

Consider returns on a fund $r_{i,t+1}$ such that

$$E_t[r_{i,t+1}] = \alpha_{it} + E_t[\mathbf{r}_{\mathbf{p},t+1}]^\top \boldsymbol{\beta}_{i,t+1}.$$

[1] The assumption of a single state variable is made for notational convenience. The model easily generalizes to multiple state variables, and even to the case where coefficients are nonlinear functions of Z_t.

Then α_{it} represents abnormal performance, just as in the static case. In what follows, we develop a method for identifying α_{it} from the data. Let e_i and f_i be fund-specific constants such that

$$E_t\left[(r_{i,t+1} - e_i - f_i Z_t)M_{t+1}\right] = 0. \tag{7}$$

We show that $\alpha_{it} = e_i + f_i Z_t$. It follows from (7) that

$$\mathrm{Cov}_t\left(a + bZ_t + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}, r_{t+1}\right) + E_t[M_{t+1}]E_t[r_{t+1} - e_i - f_i Z_t] = 0,$$

and

$$E_t[r_{t+1}] - e_i - f_i Z_t = -\frac{(\mathbf{c} + \mathbf{d}Z_t)}{E_t[M_{t+1}]}^\top \mathrm{Cov}_t(\mathbf{r}_{\mathbf{p},t+1}, r_{t+1}).$$

From (6), it follows that $e_i + f_i Z_t$ equals conditional performance α_{it}.

An advantage of this measure of performance is the ease with which it can be estimated. The coefficients a, b, $\mathbf{c}$, and $\mathbf{d}$ can be identified exactly using the following $2(N+1)$ moment conditions:

$$E\left[R^f_{t+1}\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}\right)\right] = 1 \tag{8}$$

$$E\left[R^f_{t+1}\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)\mathbf{r}_{\mathbf{p},t+1}\right) Z_t\right] = E[Z_t] \tag{9}$$

$$E\left[\mathbf{r}_{\mathbf{p},t+1}\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}\right)\right] = 0 \tag{10}$$

$$E\left[\mathbf{r}_{\mathbf{p},t+1}\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}\right) Z_t\right] = 0 \tag{11}$$

Equations (8) and (10) follow from taking unconditional expectations of (3). Equations (9) and (11) follow from multiplying both sides of (3) by Z_t and taking unconditional expectations.

The fund parameters e_i and f_i can be identified in a similar way. For excess returns r_i, the moment conditions:

$$E\left[(r_{i,t+1} - e_i - f_i Z_t)\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}\right)\right] = 0 \tag{12}$$

$$E\left[(r_{i,t+1} - e_i - f_i Z_t)\left((a + bZ_t) + (\mathbf{c} + \mathbf{d}Z_t)^\top \mathbf{r}_{\mathbf{p},t+1}\right) Z_t\right] = 0 \tag{13}$$

must hold. Given that equations (8)-(11) identify the pricing kernel, (12) and (13) exactly identify the performance variables. We estimate (8)-(13) using GMM.

2.3 Comparison to other measures

An alternative to our method is the regression-based approach of Ferson and Harvey (1999) and Ferson and Schadt (1996). Ferson and Schadt also define performance relative to a conditional pricing model (1). However, they differ in their specification of the conditional moments. Rather than assuming that the stochastic discount factor (2) is linear in the state variables, Ferson and Schadt (1998) assume that the conditional betas are linear. They estimate

$$r_{i,t+1} = \alpha_i + \delta_{1i} r_m + \delta_{2i} Z_t r_{m,t+1} + \varepsilon_{i,t+1}, \tag{14}$$

where $r_{m,t+1}$ is the return on the market, using ordinary least squares.[2] Under the null hypothesis that (1) is correct, with β_t linear in Z_t, α_i is a measure of performance.

Ferson and Harvey (1999) extend this approach to estimate conditional abnormal performance. Ferson and Harvey run the following ordinary least squares regression:

$$r_{i,t+1} = \alpha_{1i} + \alpha_{2i} Z_t + \delta_{1i} r_m + \delta_{2i} Z_t r_{m,t+1} + \varepsilon_{i,t+1}. \tag{15}$$

Like (14), (15) measures performance under the null that (1) holds, with β_t linear in Z_t. The disadvantage of this approach is that it is very sensitive to the form of the conditional moments. The result that $\alpha_{1i} + \alpha_{2i} Z_t$ equals performance is correct under the assumptions of Ferson and Harvey (1999), but fragile to deviations in their assumptions.

For example, suppose that (2) represents the stochastic discount factor. As we have shown, (1) holds, but β_t will not be linear in Z_t. Taking unconditional expectations of (3) and using the reasoning above, it follows that

$$\begin{aligned} E[r_{t+1}] &= -\frac{1}{E[M_{t+1}]}\Big(b\mathrm{Cov}(r_{t+1}, Z_t) - \mathbf{c}^\top \mathrm{Cov}(r_{t+1}, \mathbf{r}_{\mathbf{p},t+1}) - \mathbf{d}^\top \mathrm{Cov}(r_{t+1}, Z_t \mathbf{r}_{\mathbf{p},t+1})\Big) \\ &= \left[\ \beta_Z, \quad \boldsymbol{\beta}_{\mathbf{r_p}}^\top, \quad \boldsymbol{\beta}_{Z\mathbf{r_p}}^\top\ \right] \lambda \end{aligned} \tag{16}$$

For a column vector of constants λ. Because (16) must hold for the reference portfolios, as well as for the scaled portfolios $Z_t \mathbf{r}_{\mathbf{p},t+1}$, it follows that the elements of λ are expected returns. Our model thus implies an unconditional model with $2N + 1$ factors. Most importantly, our model implies that an asset will have a nonzero beta with Z_t, even if there is no abnormal performance. For this reason the Ferson and Harvey (1999) approach would be yield incorrect inferences under our assumptions. A nonzero loading on Z_t in the regression (15) could not be interpreted as conditional performance.

Our approach has several advantages over the regression-based approach. First, it clarifies the underlying assumptions on the stochastic discount factor. Given that β is a characteristic of the asset rather than the economy, it may not be possible to write down the stochastic discount factor

[2] Ferson and Schadt (1996) also consider multi-factor models, but use a single-factor model to illustrate their methodology.

that would deliver the Ferson and Schadt (1996) specification. Our method is also very flexible. We could allow the coefficients of the stochastic discount factor to be nonlinear functions of Z_t without a significant change to the methodology. While the regression-based approach delivers an estimate of the time-varying beta of a mutual fund, our approach delivers an estimate of time-varying performance that is robust to changes in the specification.

3 Data

The riskfree and factor return data come from the website of Ken French. Fama and French (1993) describe the construction of the riskfree rate series, the excess market return, the high minus low book-to-market portfolio return (HML) and the small minus big market capitalization portfolio return (SMB) are constructed. A description of the momentum portfolio return (UMD) can be found on the website of Ken French. We use a single information variable, the 12-month dividend yield on the value-weighted NYSE. The data used to construct this series come from CRSP.

The mutual fund data is from Elton, Gruber and Blake (1996). Their sample consists of the 188 common stock funds in the 1977 edition of Wiesenberger's Investment Companies that have total net assets of \$ 15 million or more and that are not restricted.[3] Their data runs from January 1977 through until December 1993. This is our sample period as well. Individual fund performance is estimated for the 146 funds that survived until the end of the sample. Consequently, the conditional performance measures for the individual funds are contaminated by survivor bias (see Brown, Goetzmann, Ibbotson and Ross, 1992, and Carpenter and Lynch, 1999, who discuss the effects of survivor conditioning). Four fund type groups are constructed using the Wiesenberger style categories, with our classifications always consistent with those employed by Elton, Gruber and Blake and Ferson and Schadt. Three of the four fund types are the Weisenberger categories, maximum capital gain, growth, and growth and income, while the fourth group includes all other funds in our sample. For disappearing funds, returns are included through until disappearance so the fund-type returns do not suffer from survivor conditioning. Funds are reclassified at the start of each year based on their category at that time.

4 Results

Tables 1, 2, and 3 show the results of our estimation for the conditional CAPM, the conditional Fama-French three-factor model, and the conditional Carhart (1997) four-factor model. The first

[3] The types of restricted funds are described in detail in Elton, Gruber and Blake (1996).

column in each table ("Cond. Pricing model with Cond. Perf.") gives the results of estimating Equations (8)-(13) for the four types of funds described above. We estimate the equations jointly, so that the noise in estimating the stochastic discount factor coefficients is taken into account when computing the standard errors. For an N-factor model, there are a total of $2(N+1+4)$ moment conditions, because there are four types of funds. For example, the conditional CAPM implies 12 moment conditions. There are exactly the same number of parameters, so system is just identified.

The second column describes the results of estimating a restricted version of the above specification. We set all the f_i to zero, and estimate system (8)-(12), so that the system remains just identified. This specification is analogous to that in Ferson and Schadt (1996) in that the underlying asset pricing model is conditional, but performance is assumed to be unconditional.

Finally, the third column describes the results of estimating an unconditional factor model, assuming that performance is unconditional. We use moment conditions (8), (10), and (12). This estimation is analogous to the unconditional regressions that have long been the focus of the literature on mutual fund performance.

The top panel in each table describes the parameter estimates for the stochastic discount factor, the middle panel describes the estimates for the fund types, and the bottom panel describes hypothesis tests. The stochastic discount factor is as described in Section 2, with $\mathbf{r_p}$ denoting the return on the CAPM for Table 1. For Table 2, $\mathbf{r_p}$ is the vector of returns on the market, the HML portfolio, and the SMB portfolio. For Table 3, $\mathbf{r_p}$ includes these three portfolios, plus the momentum portfolio.[4] The conditioning variable Z_t (the dividend-yield) is de-meaned and standardized. Thus the e coefficients can be interpreted as average performance. The coefficients f describe the change in performance (in % per month) for a one-standard deviation change in the conditioning variable.

Table 1 describes performance relative to the CAPM. Average performance, as represented by the coefficients e, is positive for some funds and negative for others. Indeed, average performance is not significantly different from zero for all specifications. The coefficient on the information variable, f, is positive for the maximum capital-gain, growth and income, and miscellaneous funds, but negative for the growth fund. The coefficient on the maximal capital gain is statistically significant, and the hypothesis that all the f coefficients are equal to zero is strongly rejected.

Tables 2 and 3 confirm that the results carry over when controlling for the fund's loadings on

[4]In all specifications, the return on the market is a gross return, not an excess return. This entails a slight modification to the moment conditions (10) and (11), namely that for the term corresponding to the market, the right-hand side should be set equal to 1, not zero. Modifying the estimation so that $R_m - R_f$ rather than R_m is used to identify the coefficients is unlikely to significantly alter the results.

size, book-to-market, and (in Table 3) momentum. Average performance e remains insignificant. Interestingly, f retains the same sign for each fund type across all three models. Namely, for all fund types except growth, the point estimate for f is positive; performance increases during business cycle troughs, as represented by a high value for the dividend-yield. For growth funds, performance increases during booms, represented by a low value of the dividend yield. The point estimates are generally insignificant, except for the f corresponding to the growth fund under the 4-factor model. However, the hypothesis that all the f coefficients are equal to zero is strongly rejected for both models.

Tables 4, 5, and 6 show the cross-sectional distribution of the t-statistics for each fund, provided we have data on that fund for the full sample. Unlike the results reported in Tables 1, 2, and 3, the results in this section are subject to survivor bias. This is reflected in a higher average value for e. Nonetheless, it is instructive to examine the fund-level properties of our statistics.

Table 4 reports statistics when performance is computed relative to the conditional CAPM. The t-statistics for f, the sensitivity of abnormal performance to the business cycle, are clearly shifted to the right relative to the null. A Bonferroni test strongly rejects the hypothesis that all of the f coefficients are zero against the alternative that one is positive. This is consistent with the findings reported above that, for most types of funds, abnormal performance increases in downturns. Tables 5 and 6 confirm that this result carries over to the three-factor and the four-factor models. For these models, the t-distribution is still shifted to the right relative to the null. However, both both tails of the distribution are significantly fatter than that of the null. A Bonferroni test confirms that there are significantly negative t-values as well as significantly positive ones.

5 Conclusions

We develop a new methodology that allows conditional performance to be a function of information available at the start of the period. This methodology uses the Euler equation restriction that comes out of the factor model rather than the beta pricing formula itself. The Euler equation restrictions that we develop can be estimated using GMM. It is also possible to allow the factor returns to have longer data series than the mutual fund series as in Stambaugh (1997). We use our method to assess the conditional performance of funds in the Elton, Gruber and Blake (1996) mutual fund data set. Using dividend yield to track the business cycle, we find that conditional mutual fund performance moves with the business cycle. In particular, we find that for all fund types except growth, abnormal performance rises during downturns, regardless of which factor model is used. For growth funds, abnormal performance rises during peaks, again regardless of the factor model.

Future work will implement the methodology using a longer series of factor returns than fund returns. This extension is likely to improve the precision of the estimates because monthly data for the factor returns date back to 1926. We also plan to include additional information variables like term spread and the cay variable of Lettau and Ludvigson (2001a) to assess whether performance is predictable at shorter frequencies.

Our results raise the question of why mutual fund performance varies over the business cycle. In particular, what are the economic mechanisms that cause managerial skill to vary? Why does this variation exhibit different patterns for different types of funds? We leave these questions to future research.

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Table 1: Conditional and Unconditional CAPM

Estimation of moment conditions (8)-(13), and subsets as described in Section 4, when there is a single factor equal to the return on the market portfolio. The state variable Z_t is the dividend yield, de-meaned and standardized. Data are monthly, beginning in 1977 and ending in 1993. Panel B refers to coefficients for fund types, as described in Section 3. Panel C reports the p-values from Wald tests of joint significance. t-statistics are in parentheses.

	Cond. Pricing Model with Cond. Perf.	Cond. Pricing Model with Uncond. Perf.	Uncond. Pricing Model
Panel A: SDF Parameters (Returns per Month)			
a	3.79	3.79	3.87
	(2.33)	(2.33)	(2.25)
b	1.57	1.57	
	(1.11)	(1.11)	
c_{MKT}	-2.75	-2.75	-2.84
	(-1.72)	(-1.72)	(-1.680)
d_{MKT}	-1.53	-1.53	
	(-1.11)	(-1.11)	
Panel B: Abnormal Performance Parameters (Return in % per Month)			
e_{mcg}	0.020	0.019	0.017
	(0.21)	(0.20)	(0.18)
f_{mcg}	0.183		
	(2.04)		
e_{grow}	0.129	0.129	0.126
	(1.72)	(1.70)	(1.66)
f_{grow}	-0.069		
	(-0.77)		
$e_{\mathrm{g\&i}}$	-0.015	-0.015	-0.021
	(-0.48)	(-0.48)	(-0.68)
$f_{\mathrm{g\&i}}$	0.032		
	(0.83)		
e_{misc}	-0.182	-0.182	-0.204
	(-1.73)	(-1.73)	(-1.88)
f_{misc}	0.037		
	(0.36)		
Avg e	-0.012	-0.012	-0.021
Panel C: Hypothesis Test P-Values			
H_o: Avg $e = 0$	0.825	0.825	0.709
H_o: All $e = 0$	0.002	0.013	0.008
H_o: All $f = 0$	< 0.000		

Table 2: Conditional and Unconditional Three-Factor Models

Estimation of moment conditions (8)-(13), and subsets as described in Section 4, when the factors are the return on the market portfolio, and the returns on the SMB and HML portfolios. The state variable Z_t is the dividend yield, de-meaned and standardized. Panel B refers to coefficients for fund types, as described in Section 3. Data are monthly, beginning in 1977 and ending in 1993. Panel B refers to coefficients for fund types, as described in Section 3. Panel C reports the p-values from Wald tests of joint significance. t-statistics are in parentheses.

	Cond. Pricing Model with Cond. Perf.	Cond. Pricing Model with Uncond. Perf.	Uncond. Pricing Model
Panel A: SDF Parameters (Returns per Month)			
a	6.45	6.45	6.50
	(2.68)	(2.86)	(2.79)
b	1.39	1.39	
	(0.82)	(0.80)	
c_{MKT}	-5.31	-5.31	-5.39
	(-2.26)	(-2.42)	(-2.36)
d_{MKT}	-1.31	-1.31	
	(-0.81)	(-0.78)	
c_{SMB}	-4.94	-4.94	-4.55
	(-1.42)	(-1.35)	(-1.32)
d_{SMB}	-5.26	-5.26	
	(-1.66)	(-1.61)	
c_{UMD}	-11.5	-11.5	-11.24
	(-2.31)	(-2.73)	(-2.80)
d_{UMD}	-0.74	-0.74	
	(-0.17)	(-0.19)	
Panel B: Abnormal Performance Parameters (Return in % per Month)			
e_{mcg}	0.042	0.042	0.055
	(0.87)	(0.91)	(1.18)
f_{mcg}	0.050		
	(1.09)		
e_{grow}	0.215	0.215	0.176
	(3.91)	(4.00)	(3.23)
f_{grow}	-0.126		
	(-1.70)		
$e_{\text{g\&i}}$	-0.011	-0.011	-0.015
	(-0.39)	(-0.37)	(-0.53)
$f_{\text{g\&i}}$	0.034		
	(0.87)		
e_{misc}	-0.186	-0.186	-0.241
	(-1.65)	(-1.62)	(-1.99)
f_{misc}	0.011		
	(0.09)		
Avg e	0.015	0.015	-0.006
Panel C: Hypothesis Test P-Values			
H_o: Avg $e = 0$	0.731	0.720	0.890
H_o: All $e = 0$	< 0.000	< 0.000	< 0.000
H_o: All $f = 0$	< 0.000		

Table 3: Conditional and Unconditional Four-Factor Models

Estimation of moment conditions (8)-(13), and subsets as described in Section 4, when the factors are the return on the market portfolio, and the returns on the SMB, HML, and momentum (UMD) portfolios. The state variable Z_t is the dividend yield, de-meaned and standardized. Panel B refers to coefficients for fund types, as described in Section 3. Data are monthly, beginning in 1977 and ending in 1993. Panel B refers to coefficients for fund types, as described in Section 3. Panel C reports the p-values from Wald tests of joint significance. t-statistics are in parentheses.

	Cond. Pricing Model with Cond. Perf.	Cond. Pricing Model with Uncond. Perf.	Uncond. Pricing Model
Panel A: SDF Parameters (Returns per Month)			
a	5.65	5.65	5.52
	(1.95)	(1.95)	(2.04)
b	2.83	2.83	
	(1.24)	(1.24)	
c_{MKT}	-4.42	-4.42	-4.32
	(-1.56)	(-1.56)	(-1.63)
d_{MKT}	-2.72	-2.72	
	(-1.24)	(-1.24)	
c_{SMB}	-4.69	-4.69	-4.48
	(-1.17)	(-1.17)	(-1.21)
d_{SMB}	-3.12	-3.12	
	(-0.93)	(-0.93)	
c_{HML}	-13.9	-13.9	-13.3
	(-2.93)	(-2.93)	(-3.25)
d_{HML}	-2.05	-2.05	
	(-0.52)	(-0.52)	
c_{UMD}	-9.58	-9.58	-9.33
	(-2.95)	(-2.95)	(-3.32)
d_{UMD}	-0.71	-0.71	
	(-0.22)	(-0.22)	

Table 3: Conditional and Unconditional Four-Factor Models (cont.)

Panel B: Abnormal Performance Parameters (Return in % per Month)

	Cond. Pricing Model with Cond. Perf.	Cond. Pricing Model with Uncond. Perf.	Uncond. Pricing Model
e_{mcg}	-0.045	-0.045	-0.038
	(-1.04)	(-1.05)	(-0.81)
f_{mcg}	0.015		
	(0.38)		
e_{grow}	0.178	0.179	0.154
	(3.41)	(3.20)	(2.61)
f_{grow}	-0.125		
	(-2.04)		
$e_{\text{g\&i}}$	-0.032	-0.032	-0.038
	(-1.11)	(-1.12)	(-1.41)
$f_{\text{g\&i}}$	0.014		
	(0.45)		
e_{misc}	-0.093	-0.094	-0.149
	(-0.81)	(-0.80)	(-1.24)
f_{misc}	0.061		
	(0.54)		
Avg e	0.002	0.002	-0.018

Panel C: Hypothesis Test P-Values

H_o: Avg $e = 0$	0.961	0.961	0.691
H_o: All $e = 0$	< 0.000	< 0.000	< 0.000
H_o: All $f = 0$	0.009		

Table 4: Cross-sectional Distribution of t-statistics for the Conditional and Unconditional CAPM

Table reports grouped t-statistics, means and standard deviations for the performance parameters (e,f) for the 146 surviving EGB funds. Coefficients and t-statistics were estimated using GMM on the moment conditions (8)-(13), and subsets as described in Section 4, when there is a single factor equal to the return on the market portfolio. The Bonferroni p-value is equal to the p-value (one-tailed) associated with the maximum or minimum t-statistic, multiplied by the number of funds. The final column reports the number of t-statistics expected in each subgroup under the null.

	Cond. Pricing Model with Cond. Perf.		Cond. Pricing Model with Uncond. Perf.	Uncond. Pricing Model	Null Distribution
	e	f	e	e	
Minimum t-statistic	-5.32	-2.59	-5.25	-5.26	
Bonferroni p-value	<0.000	0.701	<0.000	<0.000	
$t < -2.326$	7	1	6	6	1.5
$-2.326 < t < -1.960$	4	2	4	5	2.2
$-1.960 < t < -1.645$	4	0	5	2	3.6
$-1.645 < t < -1.282$	5	3	5	6	7.3
$-1.282 < t < 0.000$	41	33	40	43	58.4
$0.000 < t < 1.282$	52	63	52	49	58.4
$1.282 < t < 1.645$	13	10	14	14	7.3
$1.645 < t < 1.960$	4	10	4	4	3.6
$1.960 < t < 2.326$	3	12	4	4	2.2
$t > 2.326$	14	12	12	12	1.5
Maximum t-statistic	4.63	4.56	4.30	3.81	
Bonferroni p-value	<0.000	<0.000	0.001	0.010	
Mean Coefficient	0.040	0.106	0.040	0.036	0
Standard Deviation	0.215	0.181	0.215	0.216	1

Table 5: Cross-sectional Distribution of t-statistics for the Conditional and Unconditional Three-factor Models

Table reports grouped t-statistics, means and standard deviations for the performance parameters (e,f) for the 146 surviving EGB funds. Coefficients and t-statistics were estimated using GMM on the moment conditions (8)-(13), and subsets as described in Section 4, when the factors are the return on the market portfolio, and the returns on the SMB and HML portfolios. The Bonferroni p-value is equal to the p-value (one-tailed) associated with the maximum or minimum t-statistic, multiplied by the number of funds. The final column reports the number of t-statistics expected in each subgroup under the null.

	Cond Pricing Model with Cond Perf		Cond Pricing Model with Uncond Perf	Uncond Pricing Model	Expected Observations
	e	f	e	e	
Minimum t-statistic	-5.68	-3.54	-5.60	-5.74	
Bonferroni p-value	< 0.000	0.029	< 0.000	< 0.000	
$t < -2.326$	4	2	4	5	1.5
$-2.326 < t < -1.960$	3	3	3	1	2.2
$-1.960 < t < -1.645$	5	1	4	4	3.6
$-1.645 < t < -1.282$	4	7	5	4	7.3
$-1.282 < t < 0.000$	33	35	33	33	58.4
$0.000 < t < 1.282$	45	55	46	52	58.4
$1.282 < t < 1.645$	10	16	10	7	7.3
$1.645 < t < 1.960$	13	13	13	11	3.6
$1.960 < t < 2.326$	8	6	7	10	2.2
$t > 2.326$	21	8	21	19	1.5
Maximum t-statistic	5.62	4.02	5.66	5.51	
Bonferroni p-value	< 0.000	0.004	< 0.000	< 0.000	
Mean Coefficient	0.076	0.052	0.076	0.077	0
Standard Deviation	0.224	0.163	0.224	0.229	1

Table 6: Cross-sectional Distribution of t-statistics for the Conditional and Unconditional Four-Factor Models

Table reports grouped t-statistics, means and standard deviations for the performance parameters (e,f) for the 146 surviving EGB funds. Coefficients and t-statistics were estimated using GMM on the moment conditions (8)-(13), and subsets as described in Section 4, when the factors are the return on the market portfolio, and the returns on the SMB, HML, and momentum (UMD) portfolios. The Bonferroni p-value is equal to the p-value (one-tailed) associated with the maximum or minimum t-statistic, multiplied by the number of funds. The final column reports the number of t-statistics expected in each subgroup under the null.

	Cond Pricing Model with Cond Perf		Cond Pricing Model with Uncond Perf	Uncond Pricing Model	Expected Observations
	e	f	e	e	
Minimum t-statistic	-6.86	-3.72	-6.72	-6.67	
Bonferroni p-value	< 0.000	0.015	< 0.000	< 0.000	
$t < -2.326$	8	2	8	7	1.5
$-2.326 < t < -1.960$	4	1	4	2	2.2
$-1.960 < t < -1.645$	3	7	3	4	3.6
$-1.645 < t < -1.282$	7	7	6	2	7.3
$-1.282 < t < 0.000$	34	45	37	46	58.4
$0.000 < t < 1.282$	41	50	40	46	58.4
$1.282 < t < 1.645$	20	15	22	17	7.3
$1.645 < t < 1.960$	10	4	8	7	3.6
$1.960 < t < 2.326$	4	4	3	3	2.2
$t > 2.326$	15	11	15	12	1.5
Maximum t-statistic	4.15	3.17	4.15	3.80	
Bonferroni p-value	0.002	0.001	< 0.000	< 0.000	
Mean Coefficient	0.029	0.027	0.029	0.026	0
Standard Deviation	0.248	0.166	0.248	0.244	1