Evaluating Fixed Income Fund Performance with Stochastic Discount Factors

by

Wayne Ferson,
Darren Kisgen
and
Tyler Henry

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* Ferson is the Collins Chair in Finance at Boston College, 140 Commonwealth Ave, Chestnut Hill, MA. 02467, and a Research Associate of the NBER. He may be reached at (617) 552-6431, fax 552-0431, wayne.ferson@bc.edu, www2.bc.edu/~fersonwa. Kisgen and Henry are Ph.D students at the University of Washington School of Business Administration, Department of Finance and Business Economics Box 353200 Seattle, Washington 98195-3200, fax: 206 - 685-9392. Kisgen may be reached at kisgen@u.washington.edu. Henry may be reached at thenry@u.washington.edu. We are grateful to Warren Bailey, Edie Hotchkiss, Clifton Green, Eric Jacquier and Russ Wermers for suggestions. This paper has also benefited from workshops at Babson College, the Berkeley Program in Finance, Boston University, Brandeis, Cornell, the Federal Reserve Bank of Atlanta, New York University, Northwestern, the Pennsylvania State University, the University of Texas at Dallas, Utah and Wharton. The authors appreciate financial support from a Gutmann Center research grant and a Q-group research grant.

ABSTRACT

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We evaluate the performance of fixed income mutual funds using stochastic discount factors from continuous-time term structure models. Time-aggregation of the models for discrete returns generates additional empirical "factors," and these factors contribute significant explanatory power to empirical the models. We provide the first conditional performance evaluation for US fixed income mutual funds, conditioning on a variety of discrete ex ante characterizations of the state of the term structure and the economy. During 1985-1999 fixed income funds returned less on average than passive benchmarks that don't pay expenses, but not in all economic states. Fixed income funds typically do poorly when short term interest rates or industrial capacity utilization rates are high, and offer higher returns when quality-related credit spreads are high. We find more heterogeneity across fund styles than across characteristics-based fund groups. Mortgage funds underperform a GNMA index in all economic states. These excess returns are reduced, and typically become insignificant, when we adjust for risk using the stochastic discount factors.

1. Introduction

Recent years have witnessed an explosion of research on the performance of mutual funds, pension funds and related investment vehicles. The vast majority of this research focusses on equity-style funds. The relatively small amount of research on fixed income fund performance seems curious, given the importance of fixed income funds and assets in the economy. As of June 2002 there were 2,057 bond funds in the US, representing 25% of all mutual funds. Total assets under management by these funds totalled just over $1 trillion, or 15% of the $6.6 trillion in mutual fund assets. (These figures exclude balanced funds, which hold a mix of bonds and stocks.) Thus, fixed income funds represent a substantial economic interest. Fixed income funds have also seen rapid growth over the last decade, with the number of funds and assets under management increasing 97% and 245% respectively, since 1990.[1]

Perhaps, the relatively small amount of research on fixed income funds reflects differences in the available empirical models for fixed income and equity returns.[2] Standard models for expected equity returns lend themselves naturally to measures of risk-adjusted "abnormal" returns. For example, an "alpha" is measured as the difference between the actual average return of a fund and the expected return that is predicted by

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[1] Sources: the Investment Company Institute, *Trends in Mutual Fund Investing*, June 2002, and 2002 *Mutual Fund Handbook*.

[2] Studies that focus on US fixed income funds include Blake, Elton and Gruber (1993), Elton, Gruber and Blake (1995) and Kang (1995). Cornell and Green (1991) and Gudikunst and McCarthy (1992, 1997) examine low-grade bond funds, Stock (1982) and Kihn (1996b) examine municipal bond portfolios and Kihn (1996a) examines convertible bond funds. Duke, et al. (1993), Schadt (1996), Gallo et al. (1997), Fjelstad (1999), Detzler (1999) and Silva and Cortez (2002) study international fixed income fund performance. Dahlquist, Engstrom and Soderlind (2000) include bond and money market funds in their sample of Swedish funds, and Massa (2003) includes them in his study of fund families. Fung and Hsieh (2002) compare the styles of fixed income hedge funds and mutual funds. Additional studies include D'Antonio et al. (1997), Dietz (1981), Fong, Pearson and Vasicek (1983), Grantier (1988), Kahn (1991) and Shyy and Lieu (1994).

the model on the basis of the fund's beta risk. Fixed income models, in contrast, are typically directed at the problem of solving for the prices of derivative claims. If a portfolio is formed with unobserved weights, such as a mutual fund, the value of the portfolio of claims is difficult to model (Farnsworth, 1997).

This paper measures the performance of fixed income mutual funds in a *stochastic discount factor* (SDF) framework. The approach has several advantages. Popular term structure models identify stochastic discount factors that are easily time aggregated for monthly returns. The resulting theoretically-motivated factors are appealing, in contrast to recently popular asset pricing factors for equities that arise from empirical regularities (e.g., Fama and French, 1996).[3] Given a stochastic discount factor, a measure of abnormal return similar to the traditional alpha can be easily constructed (Chen and Knez, 1996). Given the returns generated by the fund, the "*SDF alpha*" measure of performance does not require knowledge of the portfolio weights. The stochastic discount factor approach lends itself naturally to conditional performance evaluation, where funds' alphas are conditioned on ex-ante economic states. Term structure models in particular, suggest what to condition on. This removes some of the ambiguity in instrument selection that is typical of the conditional asset pricing literature. Finally, using discrete representations of the economic state, we avoid the linear functional form assumptions that are common in the conditional asset pricing literature. Our paper is the first to use the stochastic discount factor approach and continuous-time models from the term structure literature to evaluate fund performance, and the first paper to present a conditional evaluation of US fixed income funds.

We find that the additional empirical "factors" implied by time aggregation

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[3] Critiques by Lo and MacKinlay (1990), MacKinlay (1995) and Ferson, Sarkissian and Simin (1999) illustrate the pitfalls of asset pricing factors motivated by empirical regularities.

of the continuous-time models contribute to an improved performance in explaining discrete period returns. We evaluate the SDF alphas, using passive benchmarks. The returns and volatility of the benchmarks vary significantly with the economic states. Using the benchmarks, a two-factor affine model outperforms a single factor model, for fitting the expected excess returns conditional on the states. (The single-factor affine model includes the models of Vasicek (1977) and Cox, Ingersoll and Ross (1985) as special cases.) A two-factor Brennan and Schwartz (1979) model performs similarly to the two-factor affine model. Adding a third convexity factor to the affine models adds relatively little explanatory power. Extended models with non-term structure factors perform better than the pure term structure models.

We use the SDF models to evaluate the funds' performance. During 1985-1999 fixed income funds returned less than passive benchmarks that don't pay expenses, but not in all economic states. Fixed income funds typically do poorly, relative to benchmarks, when short term interest rates or industrial capacity utilization rates are high, and offer higher relative returns when quality-related credit spreads are high. We find little cross-sectional variation in performance when funds are grouped into thirds by asset size, expense ratio, turnover, income yield, lagged return or lagged new money flows. There is more heterogeneity across fixed income fund styles. Mortgage funds underperform a GNMA index in all economic states. These excess returns are reduced, and typically become insignificant, when we adjust for risk using the stochastic discount factors.

The rest of the paper is organized as follows. Section 2 describes and motivates our empirical approach. Section 3 presents the models for the stochastic discount factors, following term structure theory, and describes how we operationalize them to handle monthly mutual fund data. We also describe how we incorporate factors in the empirical models, for default risk and other risks outside of the default-free term structure. Section 4 describes the data. Section 5 presents a comparison of linear factor models and results on the estimation of the stochastic discount factor models with passive benchmarks. Section 6 evaluates performance in our sample of mutual funds, grouped by fund characteristics. Section 7 studies performance in relation to fund style. Section 8 offers concluding remarks.

2. Empirical Methods

Most asset pricing models, including models for the term structure of interest rates, posit the existence of a stochastic discount factor, $m(\varphi)_{t+1}$, which is a scalar random variable that depends on data observed up to time t+1 and parameters φ, such that the following equation holds:

$$E_t(m(\varphi)_{t+1} R_{t+1}) = \underline{1}, \qquad (1)$$

where R_{t+1} is an N-vector of gross (i.e., one plus) "primitive" asset returns, $\underline{1}$ is a N-vector of ones and $E_t(.)$ denotes the conditional expectation, given the information in the model at time t. We say that the SDF "prices" the primitive assets if equation (1) is satisfied. Re-arranging equation (1) reveals that the expected return is determined by the SDF model as:

$$E_t(R_{t+1}) = [E_t(m_{t+1})]^{-1} + Cov_t\{ -m_{t+1}/E_t(m_{t+1}); R_{t+1}\}, \qquad (2)$$

where $Cov_t(.,.)$ is the conditional covariance given the information at time t. Thus, expected performance differs across funds in proportion to their conditional covariances with the SDF.

We allow that a mutual fund, with return $R_{p,t+1}$, may not be priced exactly by the SDF. Its SDF alpha is defined as $\alpha_{pt} \equiv E_t(m_{t+1} R_{p,t+1} - 1)$. This follows Chen and Knez

(1996) and Farnsworth, et al (2002), who show that the measure is proportional to the traditional alpha in a beta pricing representation, when the SDF is linear in the factors. In the case of the Capital Asset Pricing Model (Sharpe, 1964), the SDF is linear in the market return and α_p is proportional to Jensen's (1968) alpha.[4]

We estimate the conditional performance of a fund and the parameters of the SDF model simultaneously using the following system of moment conditions and the Generalized Method of Moments (GMM, see Hansen, 1982).

$$E\{ [m(\varphi)_{t+1} R_{t+1} -1]\otimes D_t \} = 0 \tag{3a}$$

$$E\{ [m(\varphi)_{t+1} (R_{pt+1}-R_{Bt+1}) - \alpha_p' D_t]\otimes D_t \} = 0. \tag{3b}$$

Equation (3a) says that the SDF prices the primitive returns, R_{t+1}. In equation (3b), the abnormal performance of a fund is measured relative to that of a benchmark return, $R_{B,t+1}$. The conditional alpha is $\alpha_{pt} = \alpha_p' D_t$, where D_t is the *Conditioning Dummy Variable*, which includes a constant and a vector of (0,1) variables for the discrete economic states. For example, we define a conditioning dummy variable indicating whether the term structure slope is steeper or flatter than normal, as described below. In this way, we measure the expected abnormal performance of the fund conditional on the slope of the term structure being either steep, flat, or normal.

Equation (3) follows from Equation (1) by the law of iterated expectations. Equation (1) implies $E(m_{t+1}R_{t+1} | Z_t)-1=0$ for any instrument Z_t that is public information at time *t*. A typical empirical approach with standard lagged instruments is to note that this implies $E([m_{t+1}R_{t+1}-1]\otimes Z_t)=0$, and to estimate the *unconditional* expectations. However, it

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[4] See Ferson (1995, 2002) and Cochrane (2001) for more discussion and interpretation of SDF alphas.

may not be optimal to use the instruments with a linear functional form.[5] When the instrument is a conditioning dummy variable the performance measure is "nonparametric." If the underlying economy had discrete states, the perfect conditional measure would condition the levels of risk, expected return and performance on each discrete state. In practice, using conditioning dummy variables and a small number of states we obtain simplicity and interpretability, and we are able to avoid a functional form assumption, at the cost of a coarse representation of the conditioning information. Of course, one can define more dummies to refine information, relative to the examples we use here. However, given recent studies that question the predictive ability of standard lagged instruments, our coarse representation may not entail a large cost.[6]

Farnsworth et. al. (2002) show that estimating a system like (3a, 3b) for one fund at a time produces the same point estimates and standard errors for alpha as a system that includes an arbitrary number of funds. This is convenient, as the number of available funds exceeds the number of time series, and joint estimation with all of the funds is therefore not feasible.[7] Farnsworth, et. al. also find small biases in SDF alphas, and we find small biases for fixed income benchmarks using term structure models. These biases are typically much smaller for excess returns than for raw returns. To the

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[5] The condition $E(mR-1|Z)=0$ is equivalent to $E\{(mR-1)f(Z)\}=0$ for all functions f(.). The typical linear specification assumes that $f(Z) = I \otimes Z$. See Ferson and Siegel (2003a) for a discussion of optimized functions f(.) in the context of mean variance efficiency bounds, and Ferson and Siegel (2003b) for an approach to asset pricing tests based on optimized functions for mean variance portfolios.

[6] See, for example Bossaerts and Hillion (1999), Goyal and Welch (2002), Simin (2002) and Cooper, Gutierez and Marcum (2002).

[7] Efficient GMM parameter estimates can be obtained using any subset of funds, and the individual standard errors are numerically equivalent to those in the full system. Farnsworth et. al. (2002) provide the invariance result for the special case where there is only a constant in D_t, so the alpha is a constant. The appendix to this paper refines and extends the result for a time-varying alpha.

extent that the biases are similar for the fund and the benchmark, we control it by using R_{pt+1}-R_{Bt+1} in Equation (3b). This has the additional advantage of increasing precision of the fund's alpha, because the variance of the excess return is smaller than the raw return. Of course, if the model correctly prices the benchmark return, the point estimate of the fund's alpha is not changed by the introduction of the benchmark.

3. Stochastic Discount Factor Models

We first explain how continuous-time term structure models specify the form of $m(\varphi)_{t+1}$ appropriate for a discrete-period return such as our monthly mutual fund data. The appropriate SDF involves integrals of functions of the continuous-time process. We describe how we approximate the integrals using daily data on interest rates. Finally, we describe how to combine a term structure model, designed for default-free bond returns, with a factor model for broader economic risks.

3.1 Term Structure Stochastic Discount Factor Models

Term structure models often specify a continuous-time stochastic process for the underlying state variable(s). For example, let X be the state variable following a diffusion process:

$$dX = \mu(X_t)\, dt + \sigma(X_t)\, dw, \tag{4}$$

where dw is the local change in a standard Weiner process. The state variable(s) may be the level of an interest rate, the slope of the term structure, etc. Term structure models may be based on "no arbitrage" principles or general equilibrium. In either case the model specifies the form of a market price of risk, q(X), associated with the state variable, representing the expected return in excess of the instantaneous interest rate per unit of state variable risk.

The models we study are based on time-homogeneous diffusions; that is, the functions $\mu(.)$ and $\sigma(.)$ in Equation (4) depend on time only through the level of the state variable at a point in time. In contrast, interest rate models such as Hull and White (1990) allow time variation in the functions, choosing them to fit closely the term structure of spot or forward rates observed at time t. Such models are attractive for the practice of pricing interest-dependent derivative securities, among other reasons, because by fitting the current term structure at each date the models can avoid derivative prices that allow arbitrage opportunities at the current prices. Our goal in this paper does not require us to fit precisely the structure of derivatives prices at each date. We want good models for the covariances of portfolio returns with the SDFs.

Term structure models based on Equation (4) can be shown (using Girsanov's Theorem, see Cox, Ingersoll and Ross (1985b) or Farnsworth, 1997) to imply stochastic discount factors of the following form:

$$
\begin{aligned}
{}_t m_{t+1} &= \exp(-A_{t+1} - B_{t+1} - C_{t+1}), \text{ where} \\
A_{t+1} &= \int_t^{t+1} r_s \, ds, \qquad (5) \\
B_{t+1} &= \int_t^{t+1} q(X_s) \, dw_s \\
C_{t+1} &= (1/2) \int_t^{t+1} q(X_s)^2 \, ds,
\end{aligned}
$$

where r_s is the instantaneous interest rate at time s. The notation ${}_t m_{t+1}$ is chosen to emphasize that the SDF refers to a discrete time interval, in our case one month, that begins at time t and ends at time t+1. When there are multiple state variables, there is a term like B_{t+1} and C_{t+1} for each state variable. Note that, unlike beta pricing models where the SDF is linear in the factors, the SDF in (5) is nonlinear. Dietz, Fogler and Rivers (1981) find that bond returns are nonlinearly related to bond risk factors, and argue that tests of bond portfolio performance should allow for nonlinearity.

3.2 Discretizations

To use the term structure models with monthly mutual fund data, we adopt a simple first order Euler approximation scheme for Equation (4):

$$X(t+\Delta) - X(t) \approx \mu(X_t)\Delta + \sigma(X_t)[w(t+\Delta) - w(t)]. \qquad (6)$$

The period between t and t+1 is divided into $1/\Delta$ increments of length Δ. Empirically, the period is one month, to match the mutual fund returns, and it is divided into increments of one day. For a given model, we have daily data on $X(t+\Delta)$ and $X(t)$, and the functions $\mu(X_t)$ and $\sigma(X_t)$ are specified. We can therefore infer the approximate daily values of $[w(t+\Delta) - w(t)]$ from equation (6). The terms A_{t+1}, B_{t+1} and C_{t+1} in Equation (5) are then approximated using daily data by:

$$A_{t+1} \approx \Sigma_{i=1,\ldots 1/\Delta}\, r(t+(i-1)\Delta)\, \Delta$$
$$B_{t+1} \approx \Sigma_{i=1,\ldots 1/\Delta}\, q[X(t+(i-1)\Delta)]\, [w(t+i\Delta) - w(t+(i-1)\Delta)] \qquad (7)$$
$$C_{t+1} \approx (1/2)\, \Sigma_{i=1,\ldots 1/\Delta}\, q[X(t+(i-1)\Delta)]^2\, \Delta.$$

Farnsworth (1997) and Stanton (1997) evaluate the accuracy of similar first order approximation schemes. Stanton concludes that with daily data, these approximations are almost indistinguishable from the true functions over a wide range of values, and the approximation errors should be small when the series being studied is observed monthly. He also evaluates higher order approximation schemes, and finds that with daily data they offer negligible improvements over the first order approximations.

3.3 Single-factor Models

We include a single-state variable model in the affine class, where the short term interest rate r_t is the state variable at time t:

$$dr = K(\theta - r_t)\, dt + \sigma(r)\, dw, \quad (8)$$

$$\sigma(r) = (\gamma + \delta\, r)^{1/2},$$

$$q(r) = \lambda(\gamma + \delta\, r)^{1/2}.$$

Equation (8) includes as special cases, the single-factor models of Vasicek (1977), where $\delta=0$, and of Cox, Ingersoll and Ross (1985a), where $\gamma=0$. The Euler approximations in Equation (7) specialize as follows:

$$A_{t+1} \approx \Sigma_{i=1,\ldots,1/\Delta}\, r(t+(i-1)\Delta)\, \Delta,$$

$$B_{t+1} \approx \lambda\{\, r_{t+1} - r_t - K\theta + K\, A_{t+1}) \quad (9)$$

$$C_{t+1} \approx (\lambda^2/2)\, (\gamma + \delta\, A_{t+1}).$$

In our one-factor model the SDF is given by Equation (5), with the coefficients approximated by Equation (9).

The term structure literature has directed a lot of firepower at modelling continuous-time interest rate processes like Equation (8) as accurately as possible. When the objective is to price interest-dependent derivative securities, it is important to accurately fit the stochastic process followed by state variables such as the short rate. This is because the value of an interest rate derivative may depend on the behavior of interest rates from the current date until the maturity date of the claim. Often the relation is highly nonlinear. Studies following Chan, Karolyi, Longstaff and Sanders (1992) debate whether the power in the diffusion for the spot rate in Equation (8) is 0.5, 1.0, 1.5 or some other number. Other studies ask whether the drift of the short rate process is linear as in Equation (8), or nonlinear (see, e.g, Ait-Sahalia, 1996). Indeed, Ait-Sahalia rejects most of the parametric models for the spot rate that have been proposed in the literature, by comparing their implied density functions with those observed in interest rate data.

Dai and Singleton (2002) study the ability of a class of term structure models to capture the conditional first moments of returns and yield changes for zero-coupon bonds. In our application the SDF models should align the first moments of portfolio returns with their covariances with the SDF. The portfolio returns may have different dynamics from those of zero-coupon bond returns, since fund managers change their portfolio weights over time. Therefore, while the term structure literature contains a lot of information on the performance of models for pricing derivatives and capturing the fine structure of interest rate dynamics, less is known about how useful the models are for the important task of risk adjusting managed bond portfolio returns.

3.4 Multiple-factor Models

The defining characteristic of affine term structure models is that the natural logarithms of bond prices are affine (i.e., linear with an intercept) functions of the state variables. Duffie (1996, Chapter 7) provides a general representation for affine models and discusses special cases. We include two versions of two-factor term structure models. The first is the Two-factor Affine Model:

$$dr = K_1 (\theta_1 - r_t)\, dt + [(q_1/\lambda_1)\, dw_1 + \rho(q_2/\lambda_2)\, dw_2], \qquad (10)$$

$$dl = K_2 (\theta_2 - l_t)\, dt + [\rho(q_1/\lambda_1)\, dw_1 + (q_2/\lambda_2)\, dw_2],$$

$$q_1 = \lambda_1 (\alpha_1 + \beta_1 r_t + \gamma_1 l_t)^{1/2},$$

$$q_2 = \lambda_2 (\alpha_2 + \beta_2 r_t + \gamma_2 l_t)^{1/2},$$

where $\{K_1, \theta_1, K_2, \theta_2, \lambda_1, \lambda_2, \rho, \alpha_1, \beta_1, \alpha_2, \beta_2, \gamma_1, \gamma_2\}$ are constant parameters.
In this model, l_t is the level of a long-term interest rate at time-t, and ρ is the correlation of the two diffusions. Both the drift and the squared diffusion terms are affine functions of the two state variables r_t and l_t. We implement this model in the same fashion as the one-factor affine model; the empirical model is given in Equation (13b) below.

Our second two-factor term structure model is the Brennan and Schwartz (1979) two-factor model, which falls outside of the affine class:

$$dr = r_t\,[\alpha \ln(l_t / \kappa r_t)]\,dt + r_t\,\sigma_1\,dw_1,$$

$$dl = [l_t^2 - r_t l_t + l_t\,\sigma_2^2 + q_2\,l\,\sigma_2]\,dt + l_t\,\sigma_2\,dw_2, \qquad (11)$$

$$q_1,\ q_2 \text{ are constant},$$

$$E(dw_1\,dw_2) = \rho\,dt,$$

and the fixed parameters are $\{\alpha, \kappa, \sigma_1, \sigma_2, q_1, q_2, \rho\}$. Essentially the same procedures are applied to implement this model. The reduced-form solutions for the term structure models are presented in system (13) below.

We also consider a three-factor affine model, described below, where a measure of convexity is the third factor. The motivation for the three-factor model is provided by studies such as Litterman and Sheinkman (1988), Kahn (1991), Longstaff and Schwartz (1992), Balduzzi (1994), D'Antonio, Johnsen and Hutton (1997), and Duffie and Singleton (2000).

3.5 Incorporating General Economic Risk Factors

Fixed income funds hold securities that are exposed to default risk, mortgage prepayment risk, and other risks not typically incorporated in pure term structure models.[8] Trading by fund managers may also introduce additional dynamic structure into the managed portfolio returns. Elton, Gruber and Blake (1995) use linear factor models, with as many as six factors, to evaluate fixed income fund performance. Our problem is to form an SDF that combines term structure and extra-term structure factors.

Assume that the default-free bonds held by fixed income funds can be priced by a stochastic discount factor from the term structure, $m_{1t} = \exp(-A_t - B_t - C_t)$, driven by the term structure factors, F_{1t}. The funds also hold other securities whose returns are sensitive to the term structure and a set of additional factors, F_{2t}. Partition the primitive returns as $R_t = (R_{1t}, R_{2t})$, where the R_{1t} are the default-free bonds. We assume that the factors (F_1,F_2) price the returns in R_2. The factors F_1 and F_2 may be correlated. However, we assume that the default-free bond returns in R_1 are conditionally independent of the extra-term-structure factors: $Cov_{t-1}(R_{1t};F_{2t}|F_{1t})=0$. This says that the term structure factors F_{1t} are sufficient to capture the "systematic" risks of the default-free bonds.

We derive a combined SDF based on the union of the two sets of factors. First, assume that the term structure SDF is linear in its factors: $m_{1t} = \delta_{00} + \delta_{01}'F_{1t}$. (This follows with $F_{1t} \equiv \exp(-A_t - B_t - C_t)$, $\delta_{01}=1$ and $\delta_{00}=0$.) Then, m_{1t} prices the pure default-free bonds if and only if the expected returns on the R_{1t} are linear in their betas on the F_{1t} factors (e.g. Ferson, 1995). Dropping the notation indicating the dependence of the expectations on information at time t-1, there exists an expected risk premium, λ_1 such that:

$$R_{1t} = \beta_{11} [F_{1t} + \lambda_1 - E(F_{1t})] + \varepsilon_{1t}, \text{ with } E(\varepsilon_{1t}) = E(\varepsilon_{1t}F_{1t}) = 0,$$

where β_{11} is the regression slope vector and the regression has a zero intercept. If the

[8] For a recent study of term structure models incorporating additional economic risk factors, see Ang and Piazzesi (2001). See Kahn (1991) for a decomposition of bond returns into term structure effects and other effects. See .... for an analysis of credit risk models.

combined factors price R_2, there is a regression:

$$R_{2t} = \beta_{21} [F_{1t} + \lambda_1 - E(F_{1t})] + \beta_{22} [F_{2t} + \lambda_2 - E(F_{2t})] + \varepsilon_{2t},$$

with $E(\varepsilon_{2t}) = E(\varepsilon_{2t}F_{1t}) = E(\varepsilon_{2t}F_{2t}) = 0$. The combined set of factors prices the returns in R_1, since the coefficient β_{12} in the regression of R_{1t} on F_{1t} and F_{2t} is zero, by the conditional independence assumption, and the intercept therefore is equal to zero as in the first regression. Since the beta pricing relation holds for both R_1 and R_2, using the factors F_1 and F_2, it follows (e.g. Ferson, 1995), that the combined SDF is linear in the combined set of factors: $m_t = \delta_0 + \delta_1'F_{1t} + \delta_2'F_{2t}$.

In summary, the combined SDF models are:

$$_tm_{t+1} = \delta_0 + \delta_1 \exp(-A_{t+1} - B_{t+1} - C_{t+1}) + \delta_2'F_{2t+1}. \qquad (12)$$

Given the large number of parameters in a combined model, we study the extra-term structure factors F_{2t} one at a time.

3.6 The Empirical SDF Models

The empirical SDF models are written in reduced form, as follows:

Single-factor Affine:

$$m(\varphi)_{t+1} = \exp(a + b\, A^r_{t+1} + c[r_{t+1} - r_t]) \qquad (13a)$$

Two-factor Affine:

$$m(\varphi)_{t+1} = \exp(a + b\, A^r_{t+1} + c[r_{t+1} - r_t] + d\, A^l_{t+1} + e[l_{t+1} - l_t]) \qquad (13b)$$

Two-factor Brennan and Schwartz:

$$m(\varphi)_{t+1} = \exp(a + b\, A^r_{t+1} + c\, A^l_{t+1} + d\, D^r_{t+1} + e\, D^l_{t+1} + g\, D^{rl}_{t+1}) \qquad (13c)$$

Extended Affine:

$$m(\varphi)_{t+1} = \exp(a + b\, A^r_{t+1} + c[r_{t+1} - r_t] + d\, A^l_{t+1} + e[l_{t+1} - l_t]) + \delta_2\, F_{2,t+1} \quad (13d)$$

Extended Brennan and Schwartz:

$$m(\varphi)_{t+1} = \exp(a + b\, A^r_{t+1} + c\, A^l_{t+1} + d\, D^r_{t+1} + e\, D^l_{t+1} + g\, D^{rl}_{t+1}) + \delta_2\, F_{2,t+1} \quad (13e)$$

where:

$$A^r_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, r(t+(i-1)\Delta)\, \Delta,$$

$$A^l_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, l(t+(i-1)\Delta)\, \Delta,$$

$$D^r_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, \{r(t+i\Delta)/r(t+(i-1)\Delta) - 1\},$$

$$D^l_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, \{l(t+i\Delta)/l(t+(i-1)\Delta) - 1\},$$

$$D^{rl}_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, \ln[r(t+(i-1)\Delta)/l(t+(i-1)\Delta)]\, \Delta.$$

The coefficients {a,b,c,...}, differ across the models. For identification, the coefficient δ_1 in Equation (12) is set equal to 1.0 in the reduced forms, and the coefficient δ_0 is set equal to zero. The single-factor affine model actually depends on two short rate "factors." Because of the effects of time aggregation, there is both a discrete change in the spot rate, $[r_{t+1} - r_t]$, and an average of the daily short-rate levels over the month. The single-factor affine model is nested in the two-factor affine model by setting d=e=0. The two-factor affine model depends both on the monthly changes in the long and short rates and on the average long rate and short rate values. The Brennan and Schwartz two-factor model replaces the discrete rate changes with the averages of daily relative changes, via the terms D^r_{t+1}, D^l_{t+1} and introduces the average slope measure, D^{rl}_{t+1}. Thus, the time-aggregated Brennan and Schwartz two-factor model actually uses five measured "factors" in monthly data. (We still refer to the models according to the number of theoretical factors.)

We also consider a three-factor affine model, including a convexity factor. After time aggregation, the empirical factors are the discrete change over the month, $[c_{t+1} - c_t]$, and the monthly average of the daily convexity. If c(*i*) is the daily convexity for day i, the monthly average is $A^c_{t+1} = \Sigma_{i=1,\ldots 1/\Delta}\, c(t+(i-1)\Delta)\, \Delta$.

Even with the additional factors that arise from time aggregation, the number of parameters that can be identified in the reduced form models is always smaller than the number of underlying parameters in the theoretical models. For example, the one-factor affine model of Equation (8) has five parameters (four, in the special cases of the Vasicek and Cox-Ingersoll-Ross models), while only three parameters can be identified using (13a). It would be possible to incorporate additional moment conditions, derived from the interest rate process specifications behind these models, and thereby identify additional parameters.[9] However, if the interest rate process is misspecified, then in the attempt to fit these equations the misspecification would spill over into the estimated performance measures. It is not our goal to maximize the fit to the underlying interest rate processes. To identify the covariances of funds' discrete-period returns with the factors motivated by the time-aggregated models, it is sufficient to work with the smaller number of parameters identified by (13).

4. The Data

We use several different data sets in our study. First we describe our sample of returns and attributes for US fixed income mutual funds. We then describe the conditioning dummy variables for the states of the term structure and the broader economy. Finally, we describe our measures of the risk factors, benchmarks and primitive asset returns.

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[9] For example, in the Cox-Ingersoll-Ross model the first and second moments of the discrete changes, $r_{t+1}-r_t$, conditional on the current value of the state variable r_t, may be expressed as a function of r_t and the parameters of the square root interest rate process. We could append these moment conditions to the system (13) to identify all of the model's parameters. See Farnsworth (1997) for an illustration.

4.1 Fixed Income Mutual Fund Data

The fixed income fund data are from the Center for Research in Security Prices (CRSP) mutual fund data base, and include the period from 1962 through 1999. We select funds whose objectives indicate that they are primarily US fixed income funds. We exclude municipal bond funds, money market funds and international funds.[10] The number of funds with some monthly return data in a given year varies from 53 in 1961, to 153 in 1973, to a high of 2357 in 1999. However, in our version of the database, none of the fund objective codes exist prior to 1985. Using the fund returns prior to the first code indicating a fixed income fund would present a potential look-ahead bias in fund classification. Our results for funds are therefore based on the returns after the first objective codes are observed.

In Table 1 the funds are grouped by style according to their objective codes on the CRSP files. The return for each style group in any month is an equally-weighted average of the returns of all funds, with return data for that month, whose most recently available objective codes fit into the style group. Panel A of Table 1 summarizes four groups: Government, High-yield Corporate, High-quality Corporate and Mortgage funds. In addition, we break out load and no-load funds.[11]

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[10] The objectives are the union of the following: Weisenberger objective codes CBD, CHY, GOV, LTG, or MTG; ICDI fund objective codes BQ, BY, GM, or GS; Strategic Insight fund objective codes CGN, CHQ, CHY, CIM, CMQ, CSI, CSM, GGN, GIM, GMB, GMA, GSM or IMX.

[11] Government funds include the ICDI_OBJ code GS, OBJ codes GOV or LTG, POLICY code of GS or SI_OBJ codes of GGN, GIM, or GSM. High quality funds include ICDI_OBJ code BQ, OBJ code CBD or SI_OBJ codes CGN, CIM, CSM, CMQ, CHQ, IMX or CSI. High yield funds include ICDI_OBJ code BY, OBJ code CHY or SI_OBJ code CHY. Mortgage funds include ICDI_OBJ code GM, OBJ code MTG or SI_OBJ codes GMB or GMA. All is an equal-weighted portfolio of the above. Load funds have a positive value in at least one of the following fields: FRNT_LD, DEF_LD, or REAR_LD. Noload funds have a value of zero in all three of these fields.

The summary statistics for the fund returns cover the indicated subperiods in Table 1. The returns are based on the end-of-month net asset values of the funds. Investors can trade open-end mutual funds at their net asset values per share at the close of each trading day, regardless of when the underlying assets of the funds trade. Not surprisingly, the returns look very different from equity mutual fund returns. The mean returns are all between 0.6 and 0.7% per month. The standard deviations are all on the order of 1.0 to 1.5% per month, about 1/10 the values of equity style mutual funds. The minimum return for any style in any month since 1985 is -7.23%, suffered by the high-yield fund group in August of 1998. October of 1987 was a high return month, where the All funds' portfolio earned 3.47%.

4.2 Conditioning the Models

One innovation of our study is the use of conditioning dummy variables, D_t, to condition on discrete economic states. Consider the D_t for the monthly spot rate series, r_t. We first convert the spot rate into a deviation from its average level over the last 60 months: $x_t = r_t - (1/60)\Sigma_{j=1,...60}\, r_{t-j}$. We then use the last 60 months of spot rate data to estimate a rolling standard deviation, $\sigma(r_t)$. The dummy variable $D_{t,hi}$ for a "higher than normal" level of the spot rate is then defined as the indicator function: $I\{[x_t/\sigma(x_t)] > 1\}$. Similarly, the dummy variable $D_{t,lo}$ for a "lower than normal" level of the spot rate is $I\{[x_t/\sigma(x_t)] < -1\}$. The vector conditioning dummy variable for time-t in Equation (3) is then defined as: $D_t = (1,D_{t,lo},D_{t,hi})$. If the data are approximately gaussian, we should get about 2/3 of the observations in the "normal" category, and 1/6 each in the "high" and "low" categories. Dummy variables for the other state variables are similarly defined.

Most studies of conditional performance use a similar set of lagged instruments, consisting of dividend yields, Treasury bill yields and yield spreads, following Fama and French (1988, 1989), Campbell (1987) and others. The choice of instruments in these studies is essentially ad hoc. One of the appeals of using term structure models is that the models suggest the relevant state variables. In the Cox-Ingersoll-Ross and Vasicek models, the level of the short term interest rate is the relevant conditioning information. We therefore use data for a short term spot rate to construct the conditioning dummy variable in the single-state-variable models.[12] In the two-factor models the state variables are the short rate and a long rate or term spread. We use the short rate and a term spread, the difference between a five-year and a one-month discount bond yield, in these models.[13] We also measure performance conditional on high versus low "convexity," which we measure as $y_3 - (y_5 + y_1)/2$, where y_j is the j-year discount bond yield from the CRSP FAMABY term structure files. The final state of the term structure for which we measure performance is spot rate volatility. To construct this series we use the daily spot rates within each month to compute a monthly standard deviation.[14]

Our combined models incorporate extra-term-structure risk factors together

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[12] The end-of-month value of the daily short rate is the secondary market three-month Treasury rate from the Federal Reserve H.15 release, obtained from the FRED database.

[13] The five-year yield is from the CRSP FAMABY file and the one-month yield is from the CRSP RISKFREE file. Both are converted to continuously compounded rates.

[14] One complication is that the daily three-month spot rates are highly autocorrelated. Since the interest rates refer to overlapping periods longer than one month, the data should follow a moving average process with more terms than the number of days in the month. This causes a bias in the sample variance. We approximately control this bias by modelling the autocorrelation as an AR(1) process. Let the AR(1) coefficient be ρ, let the number of daily observations in the month be T, and let $s^2(r)$ be the maximum likelihood estimator of the variance, ignoring the autocorrelation. It is easy to show that the expected value of $s^2(r)$ differs from $\sigma^2(r)$, the true variance. An unbiased estimator, in the sense that its expected value under the AR(1) assumption is $\sigma^2(r)$, may be constructed as:

$$s = s^2(r)/ [1-(1/T)-(2/T^2)\{\rho/(1-\rho)\}\{T(1-\rho^{T-1})-(1-\rho^{T-1})/(1-\rho) + (T-1)\rho^{T-1}\}].$$

We use s as our estimate of the monthly variance, where T is the number of daily observations in the month and ρ=0.990, estimated using all of the daily observations in the sample.

with the term structure factors. We include state variables related to relative yields on bonds versus stocks, inflation, credit spreads, industrial production, capacity utilization, exchange rates, short term corporate illiquidity and stock market liquidity.

We measure the relative yields on bonds versus stocks as the difference between a five year discount Treasury bond yield and the dividend yield of the CRSP value-weighted stock index.[15] Inflation as measured as the continuously compounded growth rate of the consumer price index, CPI-U, from CRSP. Credit spreads are the difference between AAA and BAA bond yields, from the Federal Reserve Database (FRED). Industrial production is the growth rate of the industrial production index (indpro.txt) and capacity utilization is a decimal fraction (tcu.txt), both from the FRED. The state of exchange rates is measured as the relative purchasing power of the dollar against the major trading partners for the US.[16] Short-term corporate illiquidity is the percentage spread of three-month high-grade commercial paper rates over three-month Treasury rates, which follows Gatev and Strahan (2003). Stock market liquidity is the measure from Lubos and Stambaugh (2003), based on price reversals.

Summary statistics for the lagged instrument data are presented in Panel B of Table 1. Perhaps the most significant feature is the high persistence of the raw instruments, as indicated by the first order sample autocorrelations. Four are in excess of 95%. This high persistence raises concerns about finite sample bias (e.g. Stambaugh, 1999) and spurious regression problems (e.g. Ferson, Sarkissian and Simin, 2003). One potential

[15] The dividend yield is computed from the with- and the without-dividend index levels and returns of the CRSP value-weighted index. It sums the preceding twelve months of dividend payments, divided by the level of the index. The Treasury yield is measured to match, as a lagging, twelve-month moving average.

[16] from January of 1999 this series is twexbmth, from the FRED. Before 1999 we use the series twexmthy, which is measured relative to the G10 countries, but is discontinued at the end of 1998. We splice the two series together by multiplying twexbmth by a constant, so that the levels of both series are the same in December of 1998.

advantage of our conditioning dummy variable approach is that the autocorrelations of the variables are always smaller than those of the underlying instruments, often substantially so. The maximum first order autocorrelation of a dummy variable in Table 1 is 93%, and all but two are below 87%.

4.3 Data for the Stochastic Discount Factors

In the term structure models, the stochastic discount factors depend on both the monthly averages of simple functions of daily interest rates, as well as changes in their end-of-month values. For example, in the single-factor, affine model, the required data are the monthly change, $r_{t+1} - r_t$, and the daily average, A^r_{t+1}, given by Equation (9). Our daily short rate series is the three-month Treasury bill rate, which is used by Stanton (1997) and evaluated by Chapman, Long and Pearson (2001). The latter finds that the errors induced by using the three-month rate to approximate an instantaneous short rate, is economically insignificant in affine term structure models. For our goal of measuring portfolio return covariances, the accuracy of this approximation should not be a first order issue.

Our daily long rate series is the seven year Treasury yield from the FRED database. We also examine empirical factors implied by a three-factor affine model, where convexity is the third factor. The daily measure of convexity is the difference between a one-year, constant maturity Treasury yield and a weighted average of the three-month and seven-year yields, from the FRED database.[17] Finally, we consider the contemporaneous value of an interest rate volatility factor, formed from the daily spot rate series as described above.

In Merton's (1973) model the current values of the state variables are the

[17] We tried a three-year constant maturity yield in place of the one year yield in the convexity measure, but it did not work as well in the regressions of Table 3. We also experimented with the ten-year and 30-year yield in place of the seven-year yield; see below.

conditioning information, and the shocks or innovations in those same state variables are the factors. We therefore measure the extra-term-structure risk factors as the growth rates or changes in the variables that serve as the lagged instruments. The additional risk factors include (1) the return of the Standard and Poors (S&P500) index, measured in excess of the one-month Treasury bill, (2) the rate of inflation, based on the CPI-U, (3) the changes in the BAA-AAA yield spread, (4) the growth rate of the industrial production index, (5) the first differences of the capacity utilization measure, (6) the log growth rate of the relative purchasing power of the US dollar, (7) a measure of short term corporate illiquidity and (8) a measure of stock market liquidity, as described above. Cornell and Green (1991) find that an equity market factor helps to price low-grade bonds.[18] Chen, Roll and Ross (1986) use risk factors similar to (1)-(4), which they "prewhiten," or transform to innovations with time series models. Since the conditioning information in our models is explicit there is no need to prewhiten the variables in a separate step. Summary statistics of the risk factors are in Panel C of Table 1.

4.4 Benchmarks and Primitive Assets

The primitive assets of the model are the returns R_t in equation (3a). They are included in order to estimate the parameters of the SDF models under the restriction that the models correctly price these assets. The primitive assets should be representative of the securities that fixed income funds hold. Farnsworth, et. al. (2002) find that SDF models for equity returns produce smaller pricing errors when a small number of primitive assets is used. Based on this evidence, we choose a small number of primitive assets, sufficient to identify the models' parameters. Our primitive asset returns are one-

[18] Gudikunst and McCarthy (1997) also find that multiple economic factors are significant in pricing low grade bond returns. See Kihn (1996b) for a similar analysis of municipal bond funds and Kihn (1996a) for convertible bond funds.

month returns on (1) a 90-day Treasury bill, (2) a twenty year Treasury bond and (3) a long-term BAA rated corporate bond. The first two series are from the CRSP mcti index files and the third is from Shearson-Lehmann.

The final data series is the benchmark return, the $R_{B,t+1}$ of equation (3b). When we study funds grouped by style we use style-based benchmarks from Shearson-Lehmann. These include a GNMA series for mortgage funds, an AAA bond index return for high-quality funds, and a BAA return index for high yield funds. When funds are grouped by characteristics, such as expense ratios, turnover, flows, etc., funds of different styles are combined. We group within each style and then combine the groups across styles, to avoid style concentrations. In these cases, we use a broad bond market aggregate as our benchmark return, the Shearson-Lehmann combined Government-Corporate bond return series. Elton, Gruber and Blake (1995) find a similar benchmark to be the most important single factor for controlling variance in their sample of fixed income fund returns. In some experiments, we also use the one-year Treasury bond return from the CRSP mcti files and the Ibbotson long-term government bond return to check robustness.

4.5 Benchmark Returns Across Economic States

Table 2 shows the sample averages and standard deviations of the gross returns for the five primitive and benchmark assets, conditional on the high, low and normal term structure and economic states. The columns are the various asset returns, from low to high risk as we move from left to right across the table; the rows correspond to the state variables. The state variable dummies are correlated, but not extremely so. The highest correlations among the low-state dummies, 1973-99, are 0.821 (short rate level and volatility), 0.635 (slope and convexity) and 0.542 (short rate level and bond-stock spread). The highest correlations among the high-state dummies are 0.737 (short rate level and volatility) followed by 0.585 (slope and convexity). The other correlations are typically much smaller.

Starting with the term structure state variables, we find that high levels of short term interest rates predict relatively high and volatile short term bond returns and low stock returns. There is a gradual transition between the two cases across the columns. The difference in the conditional mean stock return, for low versus high spot rates, is 1.7% per month and strongly statistically significant.[19] These results are generally consistent with previous evidence such as Fama and Schwert (1977) and Ferson (1989).

Table 2 suggests that a steeply sloped term structure has little information about next month's short-term bill returns, but it predicts high and low-volatility long-term bond returns, and high stock returns. The former result reflects a failure of the constant-premium version of the expectations hypothesis of the term structure (e.g. Campbell and Shiller, 1991). The latter result is consistent with consumption-based model predictions such as Breeden (1986), which emphasize a positive relation between the slope of the term structure, expected economic growth and stock returns. Harvey (1989) also finds that a steep slope predicts high economic growth. Table 2 shows that higher convexity predicts higher returns on the longer term bonds, but bears no strong relation to the level of stock returns. The former result is consistent with the convexity/return relationship described in Grantier (1988), but seems to contradict the regression results described in Shyy and Lieu (1994). High spot rate volatility is associated with higher and more volatile short term bond returns, and with lower returns on stocks and bonds exposed to default risks.

The non-term-structure state variables are also associated with interesting

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[19] The standard errors of the mean differences between the returns conditioned on the high and low states in Table 2 is approximately $0.05\ \sigma(hi)\ [1 + (\sigma(lo)/\sigma(hi))^2]^{1/2}$, where $\sigma(lo)$ is the standard deviation shown in the table for the low state. This assumes that the returns in the high and low states are uncorrelated. For the S&P500 return in the high and low spot rate states, the standard error of the mean difference is about 0.003.

return differences. High credit spreads predict high returns on stocks and lower-grade corporate bonds, consistent with Keim and Stambaugh (1986). High inflation is bad news for stocks and long-term bonds. When output growth is abnormally low, it predicts high returns, especially for the riskier assets. In the case of stocks, the difference between the low output state and the high output state is an average return of 1.4% per month. High capacity utilization predicts low returns on BAA bonds, consistent with Gudikunst and McCarthy (1997). When capacity utilization is low it predicts higher stock returns, but there is little information about short term bond returns. These general patterns are consistent with the positive relation between expected economic growth and risky asset returns, that most asset pricing models would predict if economic growth is mean reverting. The intuition is that when the real economy is performing poorly we expect it to get better, so expected growth and stock returns are high at such times. (See Chen, 1991, for related empirical evidence.)

When the purchasing power of the dollar is high, it predicts high returns for the longer term, riskier bonds. When corporate illiquidity is high, it predicts high returns on the longer term bonds and stocks, and their volatility is slightly elevated as well. Finally, states defined by the level of stock market liquidity have little predictive ability for the future returns.

5. Estimating the Stochastic Discount Factor models on Passive Benchmarks

In this section we evaluate the performance of the SDF models for pricing passive, benchmark returns. To this end, the system (3) is modified as follows:

$$E\{ [m(\varphi)_{t+1} R_{t+1} - 1] \otimes D_t \} = 0$$
$$E\{ [m(\varphi)_{t+1} R_{Bt+1} - 1 - \alpha_B' D_t] \otimes D_t \} = 0, \qquad (14)$$

where $\alpha_B'D_t$ is the conditional alpha of the passive benchmark, $R_{B,t+1}$. We conduct a series of experiments to evaluate the ability of the models to correctly price the returns of a one-year US Treasury bond and the Shearson-Lehmann Government-Corporate index. We evaluate the fit of the models informally by examining the coefficients and test statistics, paying special attention to the estimated alphas and their standard errors. A model with no bias produces a small alpha, and a model with high precision delivers a small standard error. We summarize here the results of this "prescreening" of the models, conducted before we use the models on actual mutual funds. First, we examine some linear regressions of empirical factor models.

5.1 A Comparison of Linear Factor Models

The SDFs summarized in (13) are nonlinear functions of the term structure data. Blake, Elton and Gruber (1993) and Elton, Gruber and Blake (1995) and most studies of equity funds use linear factor models, so it is interesting to compare the two approaches. The essential differences are three. First, with the linear beta pricing models the factors must be measured as excess returns to factor-mimicking portfolios, in order to get the right alpha. With SDF models this is not required, and our factors are typically not excess returns. The second difference is linearity *per se*. Linear beta models imply SDFs that are linear in the factors, whereas the term structure models imply nonlinear functions. We perform some experiments to see how models that assume the SDF is linear in the various empirical factors perform, compared with the exponential function. We simply replace the exponential function for the SDF with a linear function, using the same factors, and estimate Equation (14) on the passive benchmarks. The results are nearly identical, and any small differences seem to be in favor of the exponential specification. It does not appear that assuming the SDF to be an exponential versus a linear function of the same factors makes much of a difference.

The third feature of the term structure model SDFs is the additional variables that appear due to time aggregation. We find that the additional variables provide additional explanatory power for discrete holding period returns. Table 3 compares regressions for three default-free bond returns. TB90 is the one-month return on a three-month Treasury bill, Tbond1 is the monthly return on a one-year Treasury bond and Tbond20 is the monthly return on a twenty year Treasury bond. The regressors are measured over the same one-month period as the returns, and heteroskedasticity-consistent standard errors for the coefficients are shown on the second line.

Some of the averaged terms that arise from time aggregation are highly autocorrelated, as can be seen in Table 1. This raises concerns about bias in the regressions, due to persistent stochastic regressors. Stambaugh (1999) provides a first order adjustment for bias, and we apply the adjustment to the regression coefficients and R-squares in Table 3. We find that the effect of the adjustment is typically small, on the order of 1% of the coefficient, never exceeding 10% of the coefficient.[20] Unlike the examples for equity returns and dividend yields provided by Stambaugh, the effect of the bias adjustment here is to slightly increase the explanatory power. Campbell, Chan and Viciera (2003) also find that Stambaugh bias adjustments increase the coefficient magnitudes when bond returns are regressed on bond yields.

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[20] Stambaugh (1999) considers a regression system:

$$r_{t+1} = a + b\, Z_t + u_{t+1}$$

$$Z_{t+1} = \delta + \rho Z_t + v_{t+1},$$

with $E(u_{t+1}v_{t+1})=\sigma_{uv}$ and $E(v_t^2)=\sigma_v^2$. He shows that the OLS estimator has bias $E(b\text{-}b) = E(\rho\text{^}-\rho)\sigma_{uv}/\sigma_v^2$, where $E(\rho\text{^}-\rho) \approx -(1+3\rho)/T$. Our adjusted estimator is $b^* = b + (1+3\rho^*)\sigma_{uv}/[T\sigma_v^2]$, where $\rho^* = (T\rho\text{^}+1)/(T-3)$. This approximation treats the slope coefficients as simple regression coefficients. We compute the regression R-squares using the adjusted slopes, as the ratio of the variance of the fitted values to the variance of the dependent variable.

In affine term structure models the *conditional expected* returns of discount bonds are linear in the levels of the state variables, and such predictive regressions are explored by Dai and Singleton (2002). In Table 3 we ask the regressions to explain the *ex post* bond returns -- both the expected and the unexpected parts -- with contemporaneous values of the various factors. This can be motivated by recalling that if the SDF is approximately linear in the empirical factors there would be a linear factor model regression of bond returns on the factors, and the slope coefficients of this regression are the "betas" that describe the cross-section of the average returns. Here we describe how well the linear factor model regressions explain variance using the various empirical factors implied by continuous-time term structure models.[21]

Comparing the first two rows of Table 3 for each bond, we find that including the average short rate, as implied by the continuous-time theory, provides an improved fit relative to using only discrete spot rate changes. The adjusted R-squared for TB90 jumps from 23% to 98% when the time-averaged short rate enters the regression, and for the one-year bond the R-squared increases from 64% to 79%. However, for the twenty year bond return, introducing the average short rate slightly lowers the adjusted Rsquared. It seems sensible that refined information about the path of the short rate is more important for explaining short-term than for long-term bond returns. Given the short rate, adding the discrete second factor Δl makes a large difference in the Tbond20 regression, bumping the Rsquared from 28% to 85%, while the Δl factor does not improve the fit for TB90.

Comparing the third versus fourth rows of Table 3 reveals the marginal

[21] For any discount bond return there is an exact factor model regression that works tautologically. That model includes a yield change, a term structure slope and an interest rate level as the "factors." However, in the tautological model all three factors are maturity specific, and thus are different for different bonds. A good empirical factor model should use a small number of market-wide factors to explain bonds of different maturities.

contribution of the discrete change in convexity when discrete changes in both the short and the long rate are present. The contribution is insignificant for TB90 and the 20-year bond, but highly significant for the one-year bond, where the adjusted R-squared increases from 77% to 84%. A comparison of the fifth and sixth rows examines the incremental explanatory power of the convexity factors, Δc and A^c, given the factors implied by the two-factor affine model. The convexity factors are significant for TB90, but the change in the adjusted R-squared is modest. The convexity factors provide no marginal explanatory power for the 20-year bond return. The largest improvement is found for the intermediate, one-year maturity. In this case the convexity factors increase the adjusted R-squared from 89% to 97%.[22] It makes sense that convexity should be more important for the intermediate maturities, controlling for long and short rates, than for the long and short-maturity bonds.

The third versus fifth rows for each asset compare regressions with two discrete factors, with and without the additional time-aggregation terms suggested by the affine model. The time-aggregation terms markedly improve the regressions for the two shorter-term bonds, but are not significant for the twenty-year return. The third versus ninth rows provide a similar comparison for the three time-aggregation terms introduced by the Brennan and Schwartz model, D^r, D^l, and D^{rl}. When these variables join the regressions featuring the discrete variables Δr and Δl, they are significant for TB90 and Tbond1, but less potent than the A^r, A^l combination. For Tbond20 the Brennan and Schwartz variables remain significant, and the D^l term has a t-ratio larger than three.

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[22] We experiment by replacing the one-year with a three-year yield in the convexity measure, and the explanatory power is lower. We also replaced the seven year yield with a ten-year or a 30-year yield (the latter available starting in 1977). The longer series do not offer any marked improvements over the seven year series. In some cases the explanatory power with the ten-year and 30-year yield series is significantly worse. The 30-year yield, in particular, usually results in larger standard errors of the regressions.

The fifth versus eight rows of Table 3 provide a head-to-head comparison for each asset, of the variables suggested by the two-factor affine model (which are Δr, Δl, A^r, and A^l) versus the Brennan-Schwartz model (which are A^r, A^l, D^r, D^l, and D^{rl}). Based on the adjusted Rsquares, the affine model's variables win for TB90, by an Rsquared of 97% versus 93%. Similarly for Tbond1, the Rsquares are 89% versus 78% in favor of the affine model. For Tbond20 the two sets of variables are closer in explanatory power, at 85% versus 83%.

When we examine the SDF models' performance in pricing the passive benchmarks below, we find that the Brennan and Schwartz model is over parameterized when all of its time-aggregation terms are used.[23] The last three rows of Table 3 for each asset explore the effects of dropping one of the D-terms from the Brennan and Schwartz variable regressions. These experiments show that it is possible to drop one of the variables without degrading the explanatory power of the regressions, but give mixed signals on which one to drop. Regressions for the shorter term bonds suggest that D^l or D^{rl} can be dropped, while the twenty year bond suggests dropping either D^r or D^{rl}. We drop the D^{rl} term in the empirical models presented below.

We draw two main conclusions from this section. First, for these data, models where the stochastic discount factor is $e^{b'f}$ perform similarly to models where the SDF is b'f, using the same empirical factors, f. This does not say that term-structure motivated SDFs and linear factor models are equivalent. The additional terms that arise from the explicit time aggregation of the continuous-time models improve the explanatory power of factor model regressions for the discrete period returns.

[23] The gradient matrix becomes rank deficient.

5.3 Term Structure Models Meet Passive Benchmarks

At least two primitive assets are required in the first equation of (13) to identify the parameters of the SDF models. We use the 90-day Treasury bill and the twenty-year Treasury bond return. The second equation identifies the SDF alphas for the benchmarks, which we take to be the one-year government bond and the Shearson-Lehmann Government-Corporate index. All of the models are overidentified, and we find that Hansen's J-statistic typically rejects the models. The coefficients of the pure term structure SDF models are not estimated with very high precision. The typical t-ratio for a coefficient is about 1.2, but values between 0.11 and 3.2 are observed. Thus, for example, we could not reject the hypothesis that the long rate factors may be excluded from the two-factor affine model, reducing it to a one-factor model. Our main interest is the estimates of the conditional alphas and their precision.

Table 4 presents estimated alphas and their standard errors, conditional on the high and low values of the state variables. The first two columns present the raw conditional mean returns without risk adjustment. The far right column presents the excess-return alphas for the one-year government bond in excess of the Shearson-Lehmann government-corporate benchmark. The table shows that the conditional models explain a large fraction of the returns in most states. Even the one-factor affine model, shown in Panel A, does a reasonable job. The raw returns of the one-year government bond are 83 basis points (bp) in the high spot rate state and 55 in the low spot rate state. The conditional alphas are 3 and 7 bp, respectively. The one-factor model does not do as well on the government-corporate return, however, leaving alphas of -15 and 9 bp, respectively, in the two states.

Comparing panels A and C shows that the two-factor affine model performs better than the one-factor model. For example, the two factor model produces alphas for the government-corporate index of -8 and +9 bp per month, conditional on the spot rate states. The excess return alphas are smaller in every case.[24]

A comparison of Panel B with either panels C or D in Table 4 illustrates that the continuous time term structure models perform better than models using only the discrete factors, $[r_{t+1}-r_t]$ and $[l_{t+1}-l_t]$. For example, the discrete model shown in Panel B delivers conditional alphas for the government-corporate index equal to -12 and +14 bp in the two spot rate states, compared to the affine model's -8 and +9 bp. The excess alphas are smaller in each state when the models include the time aggregation terms. Panels C and D show that the two-factor affine and the two-factor Brennan and Schwartz models perform similarly.

5.3 Models with Extra Factors

Panel E of Table 4 summarizes extended affine models with one extra factor at a time. The models are estimated using the dummies for the spot rate, slope and the extra factor as instruments. We find that with the extra factors, the affine models and the Brennan and Schwartz models perform similarly, so we do not report results for the Brennan and Schwartz models. The coefficients, δ_2, on the additional factors are usually statistically significant, with t-ratios that average about 2.5 across the models, and values between 1.4 and 3.5 are observed. In the presence of the additional factors, the coefficients on the term structure variables often become more precise, with many t-ratios now in excess of 2.0 and values as large as 6.7 observed. Hansen's J-test still produces asymptotic p-values less than 0.05 in most cases.

The performance of the extended models on the passive benchmarks, conditional on the spot rate and term structure slopes, are typically similar for different choices of the third factor. Panel E of the table shows results for the spot rate and slope

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[24] While not shown in the table, if we ask the one-factor model to explain returns conditional on the slope, it performs much worse than the two-factor model.

states, only for the first model, where convexity is the third factor. (We use only the discrete change in convexity here.) For the remaining models we show only the results conditioned on the state variable corresponding to the extra factor.

The extended models generally work well at explaining the passive benchmark returns in the various states. For example, the high versus low output and capacity utilization states imply differences in the conditional mean returns on the order of 30 bp per month, but the excess return alphas for these states are 8 bp or smaller. The model with a stock market factor produces conditional alphas that are numerically close to zero. Based on the figures in Panel E, the average absolute ratio of the conditional alpha to the unadjusted return is 8.2% for the one-year government and 1.25% for the government-corporate returns. The precision of the alphas is generally good. The average ratio, across the models and states, of the standard error of the alpha to the standard error of the unadjusted mean return, is 21%. In some states statistically significant biases remain after risk adjustment, but the maximum bias is less than 20 bp per month. The biases for excess returns are typically smaller than for the raw returns of the passive benchmarks. In panel E, the average excess return alpha is only 2.0 basis points per month.

We conclude from this section that the term structure models can explain large fractions of the conditional mean returns on the passive benchmarks for all of the state variables. Two-factor models perform better than one-factor models, and the extended models are better yet. The affine and Brennan-Schwartz models perform similarly on the passive benchmarks. Excess return alphas are typically smaller than raw return alphas. But there are some cases where statistically significant alphas are found on passive benchmarks. High spot rates, spot rate volatility, extreme term structure slopes and high inflation states challenge the models.[25] Conditional on these states the biases

[25] Duffee (2002) also observes that affine models have trouble fitting expected returns conditional on extreme term structure slopes. He advocates "essentially affine" models, an extension we are currently exploring.

tend to be about 10 bp per month, and never exceed 20 basis points.

5.4 Additional Experiments

We estimated some of the models using three primitive assets, introducing the long-term BAA-rated corporate bond index. We find that the raw return alphas of the benchmark assets can be sensitive to the primitive assets. The excess return alphas appear less sensitive. This reinforces the impression that it is useful to measure conditional alphas in a relative form.

Overall, the models with three primitive assets do not perform better than the models with two primitive assets. Furthermore, with three primitive assets the models are not as stable numerically, and the algorithm is more prone to running off to regions of the parameter space where the gradient matrix becomes rank deficient. Overall, we prefer the models with two primitive assets. Farnsworth et al. (2002) also argue that a smaller number of primitive assets is preferred empirically.

We estimated models in which the continuous instrument, Z_t is used in Equation (13a) instead of the discrete dummy variable. These models perform markedly worse than the pure dummy variable models. One intuition for this result is that the models with the continuous instruments implicitly assume a linear relation to the instrument, while the dummy variable is a nonparametric form. Alternatively, the GMM solution with a dummy picks the parameters to fit returns in each discrete state, while the solution with a continuous instrument minimizes a different objective.

6. Fixed Income Fund Performance in Relation to Characteristics

Table 5 presents the mean excess returns of fixed income funds, grouped according to high versus low asset size, turnover, expense ratio, one-year lagged return, reported income yield, and new money flow over the previous year. Funds are grouped by characteristics within each of the style categories shown in Table 1, in order to avoid style concentrations. For example, government bond funds are likely to have lower expense ratios on average than high yield funds, and we don't want the low expense group to consist disproportionately of government funds. Within each style group we rank the funds from high to low on their expense ratios, reported for the previous year. We take the top third from each style group, and an equally weighted portfolio of these defines the high-expense fund returns for the next twelve months. The low expense group is formed from the bottom third, and the other characteristics are treated symmetrically.

The monthly returns for the characteristics-based groups in Table 5 are measured in excess of the Government-Corporate index, and the data cover the 1986-99 period (168 observations). The first row shows the unconditional mean excess returns with no risk adjustment. Most of the fund groups' average returns are slightly below the benchmark, the differences ranging from zero to 14 basis points per month across the groups. These results are reminiscent of Elton, Gruber and Blake (1993), who find negative fixed income fund unconditional alphas, similar in magnitude to expense ratios, averaging about -1% per year. Dahlquist, Engstrom and Soderlind (2000) find similar magnitudes for Swedish bond funds. This makes sense if the funds have no unconditional performance, and if the benchmark is of the same average risk, since the funds pay expenses and trading costs while the benchmark does not. The second line shows the standard errors of the means, and reveals that none of the unconditional return differences across characteristics groups are statistically significant.

Subsequent rows of Table 5 present the mean excess returns, conditional on the high versus low economic states. The excess return differences across the states tend to dwarf their differences across the fund groups, and some of the conditional mean excess returns exceed two standard errors. High short-term interest rate states predict low returns for almost all fund groups. The funds deliver relatively low returns when capacity utilization is high, with performance ranging from 11 to 24 basis points off the benchmark. Table 2 showed that the Government-Corporate benchmark returns are unusually low in high capacity-utilization states. It appears that the fund returns respond even more negatively to these states than the benchmark.

When capacity utilization is low, most of the fund excess returns are higher than average, the magnitudes similar to those of the underperformance in the high utilization state. However, in the low utilization state, the volatility of the funds' returns is unusually high as well, so the mean excess returns do not attain two standard errors. A similar pattern is observed in the low industrial production growth state, and in the high corporate liquidity state: high fund relative returns for most groups, but also high volatility. There is only one state in which we observe significant positive fund returns in excess of the benchmark, and this is the high credit spread state. The funds beat the benchmarks in this state by 16 to 90 basis points per month.

The "significance" of the results in Table 5 should be interpreted with caution. We discussed the extreme outcomes across the ten state variables, so we should account for the multiple comparisons. There are 284 conditional mean excess returns in Table 5, so we would expect about 14 of the t-ratios to be larger than 2.0 if all the mean excess returns are really zero. We find 39 t-ratios larger than 2.0 in Table 5, and the cases are certainly not independent. Still, it seems reasonable to conclude that the expected excess returns of the funds probably differ across some of the economic states that we measure.

6.1 Performance with Term Structure Models

The pure term structure models have the advantage that the relevant factors and state variables have clean support from theory, as opposed to relying on an empirical search process. Table 6 summarizes the performance results for funds grouped by characteristics, using the term structure models. We estimate the system (2) for each fund group separately. The Appendix shows this gives the same alphas as joint estimation with all funds simultaneously. The returns are measured in excess of the Government-Corporate index, which is used as R_B in Equation (3b). We report the conditional excess alphas in the high and low states, with their heteroskedasticity-consistent t-ratios in parentheses.

Table 6 includes results for the one-factor Affine model, where a comparison to the unadjusted excess returns in Table 5 is interesting. The risk adjustment cuts the performance, conditional on the high spot rate state, to about 1/2 or less of the unadjusted excess return. But alphas as large as 27 bp per month are found, and some of the t-ratios are quite large. None of the signs are changed, relative to Table 5. This means that funds' excess conditional covariances with the one-factor SDF are the right sign, but the magnitudes are too small to explain the excess returns. Not many of the differences between the high- and low-characteristics groups are statistically significant. Seven of the twelve alphas have t-ratios larger than two, but six of these are in the high spot rate state, where there are not many observations (only three in the 1986-99 period).

Table 6 also reports the results for the two-factor affine model. We found in Table 4 that the two-factor model did a better job of controlling passive benchmark excess returns than the one-factor model, and here the funds' alphas are also smaller. Under the two-factor model the largest conditional alpha in the table is 27 bp; and most are much smaller. Some of the alphas have t-ratios larger than two, such as in the high spot rate states. In no case is the performance difference between the groups of funds -- high versus low asset size, turnover, etc. -- of any statistical significance. A few cases, however, border on potential economic significance. High turnover funds underperform low turnover funds in the high slope states by about 14 bp per month. High asset size funds underperform low asset size funds in high spot rate states by about 10 bp, funds with large flows of new money outperform low flow funds by almost 20 pb, and high income yield funds underperform low income yield funds by about 25 basis points. Only the latter case is clearly larger in magnitude than the biases we observe in the excess returns of passive benchmarks. It is possible that high income yield funds sacrifice some total return performance in order to report high income yields.

We do not report results for the Brennan-Schwartz model, but the results are similar to the two-factor affine model. We conclude that the term structure models explain a substantial portion of the variation in the conditional mean returns of funds grouped by characteristics, when we condition on the level of interest rates or the slope of the term structure. We trust the results of the two-factor model more than the one-factor model, based on their performance on passive benchmarks. In most cases the magnitudes of the two-factor conditional alphas are within the range of the biases we observed for passive benchmarks, and are not statistically significant.

6.2 Fund Performance with Extra Factors

Given the empirical importance of factors outside the pure term structure, such as inflation, credit spreads and such, it makes sense to examine fund performance with models that incorporate these factors. This gives us the opportunity to examine performance conditioned on a wider range of state variables. In Table 7 we present results using the extended two-factor affine model with one additional factor at a time. The additional factors are selected to match the state variable that we condition on, and these are reported as the rows of the table. The models use dummy variables for the level and slope of the term structure and for the additional factor as instruments.

The risk adjusted performance measures in Table 7 are typically small -- closer to zero than 10 basis points in most cases -- and statistically insignificant. Most of the values are negative. This is consistent with the view that fixed income funds have essentially neutral risk adjusted performance in most economic states, net of their expenses and trading costs.[26] None of the alpha differences between high- and low-characteristics groups is statistically significant. Only five of the 144 combinations of states and fund groups generate conditional alphas with t-ratios larger than two. However, a few cases do suggest potential economic significance. In high credit spread states the alphas are 25 bp or greater for eight of the 12 fund groups. This is the only state with consistently positive risk adjusted performance. However, the t-statistics are smaller than two, which is probably explained by the high volatility of fund returns in high credit spread states. Table 5 illustrates that the standard error of the mean returns is about five times as large in high credit spread states than in low spread states. Overall, it seems that the differences in the conditional mean returns across the various states are well explained by the extended SDF models, and there is little evidence of abnormal risk-adjusted performance.

7. Fund Performance in Relation to Style

When we grouped the funds according to characteristics we used a broad benchmark, because the groups included all fund styles. However, fixed income funds may adhere more closely to style than equity funds, so controlling for style may be important. There may be more heterogeneity across fund styles than in relation to the fund characteristics examined earlier, so grouping by style may reveal performance differences obscured by the characteristics groups. This section studies fund performance by the style groups summarized in Table 1, with returns measured relative to a style-related passive benchmark. For mortgage funds we use the Shearson-Lehmann GNMA index as a benchmark. For high yield funds we use the return on the Shearson-Lehmann index of all

[26] See Berk and Green (2003) for a model in which fund flows ensure neutral performance net of expenses in equilibrium.

BAA rated bonds. For high quality funds we use the all AAA bond index return. For government securities funds, we use the Ibbotson Associates, 20-year bond return. For load funds, no-load funds and the aggregate of the styles ("all") we use the Government-Corporate index as before.

Table 8 presents the excess returns with no risk adjustments, similar to Table 5. The first three lines summarize the unconditional means and the number of monthly observations, which differ across the style groups, and the sample for each group ends in December of 1999. The range of excess returns across styles is more than twice the range we saw across the characteristics groups. In Table 5 we saw that all of the fund groups' returns were below benchmark. There is only one exception here. Over the 1990-99 period, high yield funds beat the BAA benchmark by about nine basis points per month.

The remaining rows of Table 8 summarize excess returns conditional on the high or low state variable dummies. There are a number of interesting results. Consistent with the unconditional means, there is more heterogeneity across the fund styles than we found with the characteristics groups. Mortgage funds return less than the GNMA benchmark unconditionally and in every state. The t-ratio for the difference is below -2.0 in 16 of the 24 cases shown and the magnitude of the underperformance ranges from 9 to 33 basis points per month. Overall, significant positive excess returns are rare. Cases where the t-ratios for the mean excess return exceed 2.0 include the high credit spread states (for all fund styles); also, high yield funds in three states (low short term rates, low volatility and high credit spread states).

Like in Table 5, some states predict positive excess returns that may be economically significant, but the funds' return volatilities are also higher in these states, so the means are not statistically significant. These case include the low capacity utilization and low industrial production states. The states where low excess returns are indicated in Table 8 include the high slope states, the low credit spread states, and especially the high capacity utilization states. High capacity utilization predicts underperformance ranging from 15 to 49 basis points off the benchmark. High short rates also predict low excess returns, but with only three months in the high-rate regime, these figures may not be very meaningful.

There are 168 cases in Table 8, so we would expect about eight of the t-ratios to be larger than 2.0 if all the mean excess returns are really zero. We find 45 absolute t-ratios larger than 2.0; a larger portion than in the characteristics-based groups. It seems reasonable to conclude that the expected excess returns of the funds differ across some of the economic states.

7.2 Risk Adjusted Performance by Style

Table 9 summarizes conditional SDF alphas for the funds' returns in excess of style benchmarks. Panel A applies the one-factor affine model, Panel B the two-factor affine model, panel C the two-factor Brennan and Schwartz model, and Panel D uses the extended two-factor affine models.

In Table 9, the one-factor affine model risk adjustments explain part of the excess returns, but not as much as the approximate 50% reduction we saw for the characteristics-based groups. The two-factor affine and Brennan-Schwartz models produce similar results. There is more heterogeneity in risk-adjusted performance across styles than across the characteristics groups. Six or eight of the 28 alphas have absolute t-ratios larger than two, depending on the model. Under the two-factor models the largest conditional alphas are 31 bp or less, with one exception, and most are less than 15 bp. Mortgage funds have significantly negative alphas across all the states. The significant alphas for the mortgage funds reflect their small standard errors as much as the economic magnitudes of the alphas, which range from -14 to -19 bp. However, these magnitudes are similar to the excess returns of the mortgage funds before risk adjustment.

The risk adjusted performance measures of the extended two-factor affine models are shown in Panel D. Mortgage funds have negative alphas, with t-ratios in excess of two for 13 of the 20 cases. Again, this reflects the small standard errors of the mortgage alphas: The values range from -3 to -18 bp. In high credit spread states, where the characteristics groups produced all positive alphas in excess of 25 bp, the style groups produce a range of conditional SDF alphas. Four of the seven groups have negative alphas, and Government bond funds deliver a whopping -58 bp in the high credit spread state. Overall, 28 the 140 combinations of states and fund style groups generate conditional alphas in the extended models with t-ratios larger than two. The average absolute alpha across the style groups and states is 13.2 bp. This compares with an average absolute excess return, before risk adjustment, of 22.4 bp.

8. Concluding Remarks

This paper evaluates the performance of fixed income mutual funds using stochastic discount factors from continuous-time term structure models. Conditioning the models on discrete representations of the state of the term structure and the economy, the returns and volatility of fixed-income funds and benchmarks vary significantly across the economic states. The models can explain large fractions of this variation. Additional factors arise from time-aggregation of the models for discrete returns. These factors enhance explanatory power; both in linear regressions, and in the asset pricing models, for average returns on passive benchmarks. Two-state-variable models perform better than one-state-variable models, and extended models with extra-term-structure factors are better yet. The two-factor affine and Brennan-Schwartz models perform similarly. Excess performance measures are less sensitive to the choice of benchmarks and are typically less biased than raw return measures. We evaluate fund performance in excess of benchmark returns.

We find that fixed income funds return less than passive benchmarks that don't pay expenses, but not in all economic states. The funds typically do poorly when short term interest rates are high, the slope of the term structure is steep and industrial capacity utilization is high. The largest positive excess returns are found when quality-related credit spreads are high, but the volatility of returns is also high in these states. We find little cross-sectional variation in performance when funds are grouped into thirds by asset size, expense ratio, turnover, income yield, lagged return or lagged new money flows. There is more heterogeneity across fixed income fund styles. Mortgage funds underperform a GNMA index in all of the economic states. The underperformance of mortgage-style funds survives risk adjustment, but most of the other excess returns become insignificant when we adjust for risk using the stochastic discount factors.

Appendix

Invariance of Performance Measures to the Number of Funds

We show that estimating the system (2) for a single fund produces the same alphas and standard errors as joint estimation with all funds simultaneously. This may be considered as the GMM extension of the well-known result that a seemingly-unrelated regression system with the same variables on the right hand side of each equation, may be estimated equation-by-equation (see Zellner, 197x). From equations (2a, 2b) we form the error terms:

$$u1_t = [m(\varphi)_{t+1} R_{t+1} - \underline{1}] \otimes Z_t \qquad \text{(A.1)}$$

$$u2_t = [- m(\varphi)_{t+1} (R_{pt+1} - R_{Bt+1}) + A_p D_t] \otimes D_t. \qquad \text{(A.2)}$$

Note that we allow the two equations to have different instruments; but the Z_t in Equation (A.1) can be set equal to D_t, or vice versa. The sample moment condition is $g = (1/T)\Sigma_t (u1_t{}', u2_t{}')'$. Partition $g = (g_1{}', g_2{}')'$ where $g_1 = (1/T)\Sigma_t u1_t$ is an $(n_1 x L_1)$-vector, where n_1 is the number of assets in R_t and L_1 is the dimension of Z_t. Note that only the parameters of the SDF enter g_1. Let $g_2 = (1/T)\Sigma_t u2_t$. The vector g_2 is of length $(n_2 x L)$, where n_2 is the number of funds in the system and L is the length of the vector D_t. Conformably partition the GMM weighting matrix W, where W_{11} is the upper left block, etc. The GMM estimator for the system chooses the parameter vector $\theta=(\varphi',vec(A_p)')'$ to minimize $g'Wg$, which implies:

$$g'W (\partial g/\partial\theta) = \underline{0}', \tag{A.3}$$

where $\underline{0}'$ is a $\dim(\varphi)+n_2L$ row vector of zeros. A partition of $(\partial g/\partial\theta)$ according to g_1 and g_2 (the rows) and the parameters φ and $Vec(A_p)$ (the columns) is of the form:

$$(\partial g/\partial\theta) = \begin{bmatrix} gd_{11} & 0 \\ gd_{21} & \Omega \end{bmatrix} \tag{A.4}$$

where gd_{11} and gd_{21} are full matrixes and $\Omega = I_{n2} \otimes (1/T)\Sigma_t (D_t \otimes D_t')$, is an $(n_2 x L)$-square, invertible matrix. For any value of φ, say φ^*, if we set

$$A_p(\varphi^*) = (1/T)\Sigma\{m(\varphi)_{t+1} (R_{pt+1}-R_{Bt+1})\}\otimes D_t' \, [(1/T)\Sigma_t \, A_p \, D_t \otimes D_t']^{-1},$$

then $g_2=0$ at this value. This establishes the Zellner seemingly unrelated regression result for the point estimates of alpha, taking the value of φ^* as given, since $A_p(\varphi^*)$ is the OLS estimator at this value. Using this result, the first order conditions (A.3) specialize as follows:

$$A_p - (1/T)\Sigma\{m(\varphi)_{t+1}\,(R_{pt+1}-R_{Bt+1})\}\otimes D_t'\ [(1/T)\Sigma_t\, A_p\, D_t\otimes D_t']^{-1} = 0,$$

$$g_1'W_{12}\,\Omega = 0, \qquad \text{(A.5)}$$

$$g_1'W_{11}\, gd_{11} + g_1'W_{12}\, gd_{21} = 0.$$

These conditions show that the optimal GMM estimator for φ is not independent of the funds, unless W_{12}=0. Thus, a two-step approach that estimates φ using (A.1) alone and then plugs this estimate into (A.2) is not the optimal GMM estimator.

The asymptotic covariance matrix of the parameter estimates is:

$$\text{Acov}(\Theta) = [(\partial g/\partial\Theta)'W\,(\partial g/\partial\Theta)]^{-1}. \qquad \text{(A.6)}$$

Partition this expression in conformance with (A.4), letting the matrix to be inverted, $V = (\partial g/\partial\Theta)'W\,(\partial g/\partial\Theta)$, be conformably partitioned. Using (A.4) and the fact that g_2=0, we have:

$$V_{11} = (\partial g_1/\partial\varphi)'W_{11}(\partial g_1/\partial\varphi) + 2(\partial g_2/\partial\varphi)'W_{21}(\partial g_1/\partial\varphi) + (\partial g_2/\partial\varphi)'W_{22}(\partial g_2/\partial\varphi)$$

$$V_{12} = [(\partial g_1/\partial\varphi)'W_{12} + (\partial g_2/\partial\varphi)W_{22}]\,\Omega \equiv Q\,\Omega \qquad \text{(A.7)}$$

$$V_{21} = V_{12}'$$

$$V_{22} = \Omega\, W_{22}\, \Omega.$$

The lower right block of (A.6) is the asymptotic variance of $\text{Vec}(A_p)$. Using standard expressions for partitioned matrix inversion and (A.7), this may be expressed as:

$$\text{Acov}(\text{Vec}(A_p)) = [\,\Omega W_{22}\Omega - V_{21}\, V_{11}^{-1}\, V_{12}\,]^{-1}$$

$$= \Omega^{-1}\,\{\,W_{22} - Q'V_{11}^{-1}Q\,\}^{-1}\,\Omega^{-1}. \qquad \text{(A.8)}$$

Since (A.8) is block diagonal, the asymptotic variance of the alpha for any fund is invariant to the number of funds in the system, for a given φ^*. By inspecting the upper left block of (A.6), it follows that the asymptotic variance of φ is:

$$\text{Acov}(\varphi) = [(\partial g_1/\partial\varphi)'W_{11}(\partial g_1/\partial\varphi) - (\partial g_1/\partial\varphi)'W_{12}W_{22}^{-1}W_{21}(\partial g_1/\partial\varphi)]^{-1} \quad \text{(A.9)}$$

This expression does depend on the funds, unless $W_{12}=0$.

We have shown that, for a given estimate of φ, the point estimates and asymptotic standard errors of the GMM alphas are the same with one fund in the system as with any number of funds, $n_2>1$. We now argue that the impact of the particular estimate φ^* on the alphas vanishes asymptotically. From the first equation of (A.5), the value of φ^* only affects the estimate of A_p through a second moment term. Since under standard assumptions this covariance is consistently estimated with any consistent estimator of φ in place of the true value, it follows that the estimator of A_p is consistent and has the same asymptotic distribution using any consistent estimator of φ. In practice at our sample sizes, the estimates of φ are only very slightly changed by varying the number of funds in the system, and this variation has virtually no detectable impact on the alpha for a given fund.

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Table 1

Summary Statistics for the fixed income funds, lagged instruments and factors.

Panel A: Fund returns: Equally weighted portfolios

fund group	period	nobs	mean	min	max	std	ρ_1
All	1985-99	180.0	0.006708	-0.04876	0.06134	0.01473	0.1140
Government	1985-99	180.0	0.006531	-0.06392	0.08138	0.01726	0.07556
High qual	1988-99	140.0	0.005953	-0.02130	0.03218	0.009789	0.2153
High yield	1987-99	127.0	0.006762	-0.07232	0.06947	0.01947	0.3332
Mortgage	1989-99	132.0	0.005456	-0.01602	0.02714	0.008200	0.2402
Load	1986-99	168.0	0.006510	-0.03294	0.05916	0.01279	0.07276
No Load	1986-99	168.0	0.006639	-0.03421	0.06225	0.01388	0.05838

panel B: Lagged instruments, to predict January 1968-December 1999 (384 observations)

Instrument	mean	min	max	std	ρ_1	$\rho_1(D_{hi})$	$\rho_1(D_{lo})$
Short rate	6.925	2.78	16.71	2.727	0.9709	0.8242	0.8483
Slope	0.9279	-4.25	5.208	1.340	0.8791	0.4096	0.7298
Convexity	0.1010	-0.626	0.9035	0.2025	0.7829	0.5621	0.5638
Volatility	0.6030	0.023	1.552	0.2447	0.9244	0.6516	0.6838
Credit	1.090	0.550	2.690	0.4415	0.9635	0.8596	0.7590
BS-spread	4.259	1.772	8.435	1.558	0.9903	0.8729	0.9052
Inflation	5.013	-5.412	21.47	3.917	0.6052	0.3773	0.3351
IP growth	2.889	-50.96	40.14	9.518	0.3797	0.0013	0.3407
Cap. Util	81.95	71.10	89.20	3.529	0.9798	0.8573	0.8542
Xchange	103.3	80.97	158.4	15.43	0.9890	0.9277	0.8386
Corp Iliq.	0.0805	-0.099	1.149	0.135	0.7388	0.3424	0.0939
Stock Liq.	-0.03116	-0.469	0.203	0.059	0.2120	0.0874	0.1439

Panel C: Risk factors, January 1973 - December, 1999 (324 observations)

factor	mean	min	max	std	ρ_1
A^r	0.0006609	0.0002770	0.001579	0.0002600	0.9747
$r_{t+1} - r_t$	9.389E-09	-0.0003905	0.0002434	6.238E-05	0.1145
A^l	0.006614	0.003539	0.01234	0.001866	0.9845
$l_{t+1} - l_t$	6.652E-07	-0.001659	0.001634	0.0003637	0.1330
D^r	0.002073	-0.3593	0.2601	0.07080	0.07691
D^l	0.001028	-0.1680	0.1695	0.04789	0.1321
D^{rl}	-2.228	-2.733	-1.842	0.1848	0.9665
dconvex	-0.0002022	-0.5975	0.8945	0.1359	-0.3745
vol	0.001811	0.0007027	0.004515	0.0007408	0.9326

table 1, page 2

Panel C Risk factors, continued...

factor	mean	min	max	std	ρ_1
cpi	0.004245	-0.004510	0.01789	0.003460	0.6335
dqual	-5.454E-07	-0.0004584	0.0005498	0.0001026	0.1888
ipx	0.002262	-0.04247	0.03345	0.007909	0.3875
dcap	-0.01698	-3.600	2.600	0.6378	0.3777
spxret	0.004143	-0.2838	0.1392	0.04567	0.01172
ddollar	-0.000559	-0.06248	0.07049	0.02157	0.3319
dcliq	-0.002771	-0.4627	0.2809	0.06954	-0.2611
dsliq	-1.948E-05	-0.4394	0.4417	0.07464	-0.5134

Notes: Nobs is the number of monthly observations and ρ_1 is the sample, first order autocorrelation. The instruments are as follows. The short rate is the bid yield to maturity on a 90-day Treasury bill. Slope is the difference between and five-year and a one-month discount Treasury yield, y_5-y_1. Convexity is $y_3 - (y_5 + y_1)/2$. Credit is the difference between a BAA and an AAA corporate bond index yield. BS-spread is the difference between a lagging, twelve month moving average of monthly values of y_5 and the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. IP growth is the monthly growth rate of the seasonally-adjusted industrial production index. Cap. Util is a measure of industrial capacity utilization and Xchange is a trade-weighted purchasing power index for the U.S. dollar. Corp. Illiq. is the percentage spread of prime commercial paper over three-month Treasury rates, a measure of short term corporate illiquidity. Stock Liq. is a measure of stock market liquidity based on price reversals in response to trading volume, from Lubs and Stambaugh (2003). The factors in Panel C are measured in continuously compounded monthly decimal fractions and are defined as follows. Avshort and avlong are the monthly averages of daily short and long term interest rates. Dshort and dlong are the first differences of the end-of-month values. A^r is daily approximation for the integral of the short rate over the month, A^l is the integral of the long rate, D^{rl} is the integral of the log of their ratio. D^r is the cumulative percentage change in the short rate and D^l is the cumulative percentage change in the long rate. Vol is the monthly spot rate volatility, estimated from daily data within the month. Dconvex is the first difference of the convexity measure. Cpi and ipx are the monthly growth rates of the consumer price index and industrial production index. Dqual is the first difference of the BAA less AAA yield spread. Dcap is the first difference in the capacity utilization measure, and ddollar is the growth rate in the relative purchasing power of the US dollar. Dcliq is the change in short term corporate illiquidity and dsliq is the change in stock market liquidity.

Table 2

Primitive and Benchmark Return Statistics in Different Economic States. The sample period is January, 1973 through December, 1999 (N=324). Returns are one plus the rate of return, in monthly decimal fractions.

Asset Return:		90-day Bill		One-year Bond		20-year Bond		Govcorp Return		BAA Return		S&P500	
State	N	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
high Short rate	55.00	1.009	0.003541	1.008	0.01101	1.002	0.03825	1.003	0.02655	0.997	0.04102	0.998	0.04800
normal	190.0	1.006	0.002145	1.007	0.005377	1.008	0.02732	1.008	0.01591	1.011	0.02584	1.013	0.04575
low	79.00	1.005	0.001512	1.006	0.003600	1.009	0.03320	1.008	0.01567	1.010	0.01984	1.015	0.03899
high Slope	43.00	1.006	0.002472	1.007	0.005510	1.019	0.02641	1.014	0.01480	1.022	0.02492	1.019	0.03612
normal	195.0	1.006	0.002516	1.006	0.005717	1.007	0.03085	1.007	0.01701	1.009	0.02599	1.011	0.04740
low	86.00	1.007	0.003134	1.007	0.008112	1.003	0.03191	1.004	0.02102	0.999	0.03152	1.006	0.04258
high Convexity	36.00	1.007	0.004122	1.008	0.007910	1.017	0.03185	1.014	0.01938	1.021	0.03119	1.012	0.03915
normal	209.0	1.006	0.002235	1.006	0.005071	1.006	0.02897	1.007	0.01600	1.008	0.02537	1.010	0.04402
low	79.00	1.007	0.002970	1.007	0.008441	1.007	0.03482	1.005	0.02201	1.002	0.03202	1.012	0.04964
high Volatility	60.00	1.009	0.003697	1.009	0.01108	1.007	0.04041	1.006	0.02789	1.001	0.04313	1.004	0.05238
normal	190.0	1.006	0.002052	1.006	0.004915	1.008	0.02723	1.008	0.01506	1.010	0.02427	1.012	0.04500
low	74.00	1.004	0.001453	1.005	0.003648	1.007	0.03134	1.007	0.01533	1.010	0.02084	1.014	0.03717
high Credit	62.00	1.008	0.003816	1.008	0.008796	1.006	0.03340	1.008	0.02210	1.013	0.03685	1.021	0.04541
normal	168.0	1.006	0.002477	1.006	0.006361	1.006	0.03229	1.006	0.01828	1.006	0.02734	1.007	0.04963
low	94.00	1.005	0.001861	1.006	0.004083	1.011	0.02621	1.008	0.01473	1.009	0.02246	1.011	0.03336
high BS-spread	71.00	1.008	0.004119	1.009	0.01089	1.009	0.04093	1.009	0.02690	1.010	0.04106	1.012	0.04578
normal	165.0	1.006	0.001692	1.006	0.004410	1.007	0.02627	1.007	0.01460	1.008	0.02315	1.012	0.03925
low	88.00	1.005	0.001711	1.005	0.003899	1.008	0.02986	1.007	0.01523	1.007	0.02406	1.007	0.05344
high Inflation	47.00	1.007	0.003382	1.007	0.01072	1.005	0.04027	1.005	0.02752	1.000	0.04146	1.000	0.06256
normal	225.0	1.006	0.002551	1.006	0.004936	1.006	0.02801	1.006	0.01529	1.008	0.02471	1.011	0.04211
low	52.00	1.006	0.002765	1.008	0.006768	1.015	0.03275	1.012	0.01844	1.017	0.02574	1.019	0.03521
high IP growth	40.00	1.006	0.002459	1.006	0.004662	1.004	0.02233	1.005	0.01289	1.004	0.02061	1.004	0.03466
normal	238.0	1.006	0.002728	1.006	0.006276	1.007	0.03113	1.007	0.01807	1.008	0.02792	1.011	0.04613
low	46.00	1.007	0.002948	1.009	0.007979	1.011	0.03593	1.010	0.02196	1.011	0.03474	1.018	0.04557
high Cap.Util	70.00	1.006	0.001486	1.006	0.004268	1.008	0.02701	1.007	0.01419	1.008	0.01985	1.008	0.04909
normal	186.0	1.006	0.002951	1.006	0.006485	1.006	0.03165	1.006	0.01840	1.006	0.02835	1.009	0.04144
low	68.00	1.006	0.003185	1.008	0.007796	1.009	0.03283	1.010	0.02077	1.016	0.03357	1.020	0.04860
high Xchange	72.00	1.008	0.003367	1.009	0.007365	1.013	0.03619	1.011	0.02083	1.015	0.03321	1.010	0.04416
normal	141.0	1.005	0.002615	1.006	0.006108	1.009	0.02888	1.008	0.01616	1.010	0.02250	1.014	0.03937
low	111.0	1.006	0.001817	1.005	0.005630	1.001	0.02885	1.003	0.01795	1.002	0.03018	1.008	0.05146
high Corp. Iliq	34.0	1.006	0.002910	1.007	0.006444	1.011	0.03135	1.010	0.02010	1.014	0.03278	1.024	0.05654
normal	270.0	1.006	0.002766	1.007	0.006464	1.007	0.03115	1.007	0.01798	1.008	0.02789	1.009	0.04282
low	20.00	1.006	0.002403	1.004	0.004962	1.001	0.02681	1.002	0.01615	1.005	0.02370	1.012	0.04808

Asset Return:		90-day Bill		One-year Bond		20-year Bond		Govcorp Return		BAA Return		S&P500	
State	N	mean	std	mean	std	mean	std	mean	std	mean	std	mean	std
high Stock Liq.	46.00	1.006	0.002525	1.006	0.005180	1.008	0.03230	1.007	0.01675	1.009	0.02683	1.011	0.03765
normal	238.0	1.006	0.002566	1.007	0.005856	1.007	0.02904	1.007	0.01732	1.009	0.02711	1.011	0.04588
low	40.00	1.007	0.003885	1.008	0.009962	1.007	0.03968	1.007	0.02393	1.005	0.03562	1.010	0.04708

Notes for Table 2: For each state variable, high (low) values are defined to occur when the difference between the current level of the variable and a lagged, 60-month moving average is more than one 60-month moving standard deviation above (below) zero. Normal is defined as the values that are neither high nor low. The instruments are as follows. The short rate is the bid yield to maturity on a 90-day Treasury bill. Slope is the difference between and five-year and a one-month discount Treasury yield, y_5-y_1. Convexity is $y_3 - (y_5 + y_1)/2$. Credit is the difference between a BAA and an AAA corporate bond index yield. BS-spread is the difference between a lagging, twelve month moving average of monthly values of y_5 and the annual dividend yield of the CRSP value-weighted stock index. Inflation is the percentage change in the consumer price index, CPI-U. IP growth is the monthly growth rate of the seasonally-adjusted industrial production index. Cap. Util is a measure of industrial capacity utilization and Xchange is a trade-weighted purchasing power index for the U.S. dollar. Corp. Illiq. is the percentage spread of prime commercial paper over three-month Treasury rates, a measure of short term corporate illiquidity. Stock Liq. is a measure of stock market liquidity based on price reversals in response to trading volume, from Lubs and Stambaugh (2003).

Table 3

A comparison of linear factor model regressions for default-free bond returns. TB90 is the one-month gross return on a 90-day Treasury bill, Tbond1 is a one-year Treasury bond and Tbond20 is the monthly gross return on a twenty year Treasury bond. The regressors are measured for the same month as the return, and heteroskedasticity-consistent standard errors are shown on the second line. The intercepts are shown in the first column. The other regressors are indicated as follows: Δr is the change in the 90-day spot rate, Δl is the change in the seven-year Treasury yield, Δc is the discrete change in the monthly convexity measure, A^r is the daily average spot rate over the month, A^l is the daily average seven year yield, A^c is the daily average of the convexity measure, D^r is the daily average change in the spot rate, D^l is the daily average change in the yield, and D^{rl} is a daily average slope, measured using the three-month and seven-year yields. Rsq is the adjusted R-squared. The sample period is January, 1973 through December, 1999 (N=324). Returns are one plus the rate of return, in monthly decimal fractions. The coefficients and standard errors, exepting the intercept, are multiplied by 100.

Bond Return:		Δr	Δl	Δc	A^r	A^l	A^c	D^r	D^l	D^{rl}	Rsq
TB90	1.006	-20.77									0.230
	0.0001	3.82									
	1.000	-20.97			8.487						0.978
	0.0001	0.78			0.190						
	1.006	-22.22	3.686								0.230
	0.0001	4.347	5.585								
	1.006	-28.69	14.01	-16.31							0.238
	0.0001	6.344	8.336	11.40							
	0.9998	-20.34	-1.208		7.602	1.313					0.984
	0.0001	0.937	1.251		0.376	0.389					
	0.9998	-23.94	4.393	-8.531	8.433	0.420	4.750				0.989
	0.0001	1.086	1.595	1.977	0.294	0.353	1.299				
	0.9995				6.679	2.226					0.706
	0.0004				0.960	1.109					
	1.000				4.696	3.889		-1.681	-0.110	0.180	0.929
	0.0003				1.568	1.446		0.126	0.11	0.089	
	1.007	-20.48	-0.635					-0.164	0.146	0.818	0.576
	0.0002	7.825	14.16					0.542	1.080	0.049	

Bond Return:		Δr	Δl	Δc	A^r	A^l	A^c	D^r	D^l	D^{rl}	Rsq
TB90	0.9997				7.127	1.722		-1.669	-0.131		0.932
	0.0002				0.549	0.627		0.126	0.118		
	1.000				4.640	3.927		-1.722		0.184	0.928
	0.0003				1.554	1.438		0.127		0.089	
	0.9997				5.469	3.415			-1.661	0.103	0.785
	0.0004				2.265	2.050			0.267	0.122	
Tbond1	1.007	-80.07									0.639
	0.0002	7.468									
	1.002	-80.24			7.168						0.736
	0.0006	6.203			0.930						
	1.007	-50.80	-74.33								0.767
	0.0002	6.702	7.073								
	1.007	-91.25	-9.689	-102.1							0.844
	0.0001	6.658	9.076	11.46							
	0.9996	-48.82	-78.25		4.363	5.131					0.893
	0.0005	5.001	5.702		1.492	1.513					
	0.9996	-89.08	-13.85	-100.3	5.132	4.349	11.57				0.968
	0.0003	3.488	4.395	5.957	0.727	0.859	3.089				
	0.9985				-0.462	9.330					0.086
	0.0016				4.075	4.451					
	1.000				-5.179	13.65		-4.486	-5.980	0.534	0.764
	0.0009				5.849	5.324		0.555	0.669	0.332	
	1.008	-47.91	-102.2					-0.152	2.321	0.657	0.809
	0.0003	10.54	17.99					0.687	1.406	0.089	
	0.9994				2.103	7.152		-4.451	-6.044		0.763
	0.0008				2.116	2.338		0.555	0.669		
	1.001				-8.237	15.76		-6.725		0.724	0.645
	0.0011				6.760	6.273		0.699		0.368	

table 3, page 3

Bond Return:		Δr	Δl	Δc	A^r	A^l	A^c	D^r	D^l	D^{rl}	Rsq
	0.9994				-3.107	12.38			-10.12	0.331	0.600
	0.0013				7.464	6.664			1.087	0.405	
Tbond20	1.007	-257.3									0.282
	0.0015	31.45									
	1.008	-257.3			-1.505						0.280
	0.0041	31.53			6.013						
	1.007	38.96	-752.5								0.852
	0.0007	17.79	34.72								
	1.007	56.67	-780.8	44.69							0.851
	0.0007	35.49	53.52	66.11							
	1.000	40.80	-753.4		-4.219	12.88					0.854
	0.0027	17.85	34.07		6.834	7.041					
	0.9997	60.81	-784.6	47.88	-7.870	16.80	-22.07				0.854
	0.0026	36.78	56.46	68.99	7.876	7.518	21.94				
	0.9967				-28.67	31.48					0.009
	0.0077				16.84	20.60					
	1.000				-25.09	32.49		0.200	-61.88	0.900	0.796
	0.0043				22.17	20.29		1.807	3.027	1.362	
	1.007	21.31	-600.5					0.968	-13.80	0.013	0.854
	0.0010	52.86	88.39					4.378	6.719	0.359	
	0.9987				-13.66	22.30		0.255	-61.98		0.796
	0.0037				7.787	9.210		1.803	3.034		
	1.004				-56.74	54.47		-22.96		2.837	0.272
	0.0071				37.09	35.35		3.151		2.177	
	1.000				-25.13	32.55			-61.69	0.897	0.796
	0.0043				22.30	20.36			2.843	1.369	

Table 4
Conditional Alphas on Passive Benchmarks

GMM estimation of the system (12), for the various models in Equation (13). The benchmark returns are a one-year Treasury bond, with conditional means in the column labelled rb1, and the Shearson-Lehmann government corporate aggregate bond index, denoted rgovcor. The means and alphas are conditioned on higher than average or lower than average values of the various state variables, as described in the text. Standard errors of means and alphas are shown below. The conditional alphas are shown as α. The excess alpha is the alpha for the return difference. The sample period is January, 1973 through December, 1999 (324 observations).

state variable	hilo	rb1	rgovcor	α_{rb1}	$\alpha_{rgovcor}$	excess alpha
Panel A: One-factor Affine Model						
Short	high	0.00825	0.00329	0.000267	-0.00149	0.00175
rate		0.00148	0.00358	0.000684	0.00111	0.000759
	low	0.00555	0.00764	0.000660	0.000941	-0.000281
		0.000405	0.00176	0.000201	0.000452	0.000337
Panel B: Discrete Two-factor Model						
Short	high	0.00825	0.00329	0.000608	-0.00123	0.00184
rate		0.00148	0.00358	0.000599	0.000906	0.000665
	low	0.00555	0.00764	0.000904	0.00143	-0.000522
		0.000405	0.00176	0.000163	0.000360	0.000304
Slope	high	0.00744	0.0143	0.000250	0.00160	-0.00135
		0.000840	0.00226	0.000383	0.000568	0.000460
	low	0.00686	0.00385	0.000514	-0.000778	0.00129
		0.000875	0.00227	0.000336	0.000527	0.000447
Panel C: Two-factor Affine Model						
Short	high	0.00825	0.00329	0.000796	-0.000807	0.00160
rate		0.00148	0.00358	0.000611	0.00105	0.000756
	low	0.00555	0.00764	0.000698	0.000876	-0.000177
		0.000405	0.00176	0.000194	0.000446	0.000336

table 4, page 2

state variable	hilo	rb1	rgovcor	α_{rb1}	$\alpha_{rgovcor}$	excess alpha
Slope	high	0.00744	0.0143	0.000324	0.00154	-0.00121
		0.000840	0.00226	0.000380	0.000544	0.000451
	low	0.00686	0.00385	0.000600	-0.000508	0.00111
		0.000875	0.00227	0.000373	0.000643	0.000503
Panel D: Two-factor Brennan and Schwartz model						
Short rate	high	0.00825	0.00329	0.000520	-0.00114	0.00166
		0.00148	0.00358	0.000617	0.00108	0.000767
	low	0.00555	0.00764	0.000665	0.000807	-0.000142
		0.000405	0.00176	0.000202	0.000453	0.000334
Slope	high	0.00744	0.0143	0.000281	0.00152	-0.00124
		0.00084	0.00226	0.000374	0.000552	0.000439
	low	0.00686	0.00385	0.000522	-0.000600	0.00112
		0.000875	0.00227	0.000370	0.000681	0.000510
Panel E: Extended Two-factor Affine Models						
Short rate	high	0.00825	0.00329	0.000516	-0.00117	0.00169
		0.00148	0.00358	0.000578	0.00104	0.000760
	low	0.00555	0.00764	0.000692	0.000988	-0.000296
		0.000405	0.00176	0.000190	0.000441	0.000330
Slope	high	0.00744	0.0143	0.000270	0.00152	-0.00125
		0.00084	0.00226	0.000369	0.000551	0.000439
	low	0.00686	0.00385	0.000486	-0.000683	0.00117
		0.000875	0.00227	0.000352	0.000666	0.000506

state variable	hilo	rb1	rgovcor	α_{rb1}	$\alpha_{rgovcor}$	excess alpha
Panel E: Extended Two-factor Affine Models, Continued...						
Convexity	high	0.00841	0.0137	0.000654	0.00166	-0.00101
		0.00132	0.00323	0.000530	0.000829	0.000571
	low	0.00698	0.00539	0.000346	-0.000680	0.00103
		0.000950	0.00248	0.000416	0.000667	0.000451
Volatility	high	0.00895	0.00609	0.000721	-0.00117	0.00189
		0.00143	0.00360	0.000601	0.00103	0.000730
	low	0.00523	0.00685	0.000646	0.000954	-0.000308
		0.000424	0.00178	0.000208	0.000471	0.000344
Credit	high	0.00832	0.00810	0.00125	0.00195	-0.000699
		0.00112	0.00281	0.000490	0.000843	0.000601
	low	0.00595	0.00801	0.000167	-0.000500	0.000667
		0.000421	0.00152	0.000210	0.000489	0.000374
S&P 500	high	0.00872	0.00859	0.000653	0.000597	5.61E-05
		0.00129	0.00319	0.000526	0.000817	0.000510
	low	0.00545	0.00679	0.000583	0.000605	-2.20E-05
		0.000416	0.00162	0.000217	0.000642	0.000530
Inflation	high	0.00743	0.00505	0.000841	-0.000579	0.00142
		0.00156	0.00401	0.000629	0.00132	0.000907
	low	0.00797	0.0119	0.000931	0.00151	-0.000576
		0.0009	0.00256	0.000439	0.000799	0.000510
IP Growth	high	0.00576	0.00508	0.000418	0.000379	3.91E-05
		0.000737	0.00204	0.000320	0.000834	0.000745
	low	0.00853	0.00970	0.00103	0.000652	0.000381
		0.00118	0.00324	0.000527	0.00107	0.000743

state variable	hilo	rb1	rgovcor	α_{rb1}	$\alpha_{rgovcor}$	excess alpha
Panel E: Extended Two-factor Affine Models, Continued...						
Cap Util	high	0.00596	0.00696	-4.29E-05	-2.25E-05	-2.03E-05
		0.000510	0.00170	0.000265	0.000474	0.000355
	low	0.00788	0.00968	0.00139	0.00218	-0.000792
		0.000945	0.00252	0.000363	0.000705	0.000509
Xchange	high	0.00931	0.0114	0.000783	0.000761	2.26E-05
		0.000868	0.00245	0.000341	0.000526	0.000352
	low	0.00545	0.00309	0.000208	1.92E-05	0.000188
		0.000534	0.00170	0.000313	0.000656	0.000473

Table 5

Fixed Income Fund Excess Returns

Returns in excess of the Government-Corporate bond index are shown for equal-weighted portfolios of funds grouped on high versus low asset size, turnover and expense ratios. High-asset funds are those in the top third, while low asset funds are in the bottom third, etc. The excess returns are decimal fractions per month, for the 1986-99 period (168 observations); the flow group has twelve fewer. The first two rows report the unconditional sample means and standard deviations of the mean excess returns. Subsequent rows report excess returns conditional on various economic states, as measured by dummy variables. Figures larger than two standard errors of the mean are in bold. Nobs is the number of monthly observations for the state.

fund grouping:	asset high	asset low	turnover high	turnover low	expense high	expense low
State Nobs						
Uncond.	-2.673E-05	-0.0001190	-0.0002778	3.228E-05	-0.0003624	-7.061E-05
168	0.0005427	0.0005818	0.0005522	0.0005281	0.0006179	0.0004838
hi short rate	**-0.003959**	-0.0008446	**-0.004803**	**-0.002016**	**-0.003499**	**-0.005232**
3	0.0009229	0.001221	0.001363	0.0007958	0.0006687	0.001980
lo short rate	9.650E-06	-0.0004889	-0.0002193	0.0004227	-0.0004340	0.0002644
64	0.001091	0.001121	0.001104	0.001020	0.001167	0.0009213
hi slope	-0.001849	-0.002604	-0.003060	-0.001943	-0.002994	-0.002605
17	0.001819	0.001919	0.002323	0.001721	0.002093	0.001548
lo slope	-0.0002245	0.0002477	-0.0001115	-0.0003615	-0.0003707	-0.0004686
46	0.0005937	0.0006734	0.0006907	0.0006124	0.0006591	0.0007309
hi convexity	-0.001468	-0.001249	-0.0009150	-0.001351	-0.001942	-0.000822
15	0.001974	0.001283	0.001310	0.001845	0.002174	0.001155
lo convexity	-0.001356	-0.0008181	-0.001438	-0.0007417	-0.001894	-0.001148
43	0.0008715	0.0009511	0.0009648	0.0007555	0.001085	0.0008063
hi volatility	-0.0008522	-0.0007195	-0.001107	-0.0006918	-0.001288	-0.001104
11	0.001209	0.001412	0.001370	0.001350	0.001300	0.001624
lo volatility	-0.0001940	-0.0007226	0.0001091	7.038E-05	-0.0004580	3.843E-05
62	0.001045	0.001046	0.0009121	0.001018	0.001126	0.0008534
hi credit	**0.005819**	**0.005923**	**0.005131**	**0.006020**	**0.006491**	**0.005467**
14	0.002557	0.002601	0.002309	0.002633	0.003026	0.002067
lo credit	-0.001017	-0.0007691	**-0.001024**	**-0.001259**	**-0.001293**	**-0.001155**
78	0.000542	0.0004814	0.0004822	0.0005078	0.0005669	0.0004916

table 5, page 2

fund grouping:	asset high	asset low	turnover high	turnover low	expense high	expense low
hi BS spread	-0.001167	-0.001588	-0.001541	-0.001502	-0.001485	-0.001636
16	0.001016	0.001157	0.001149	0.001079	0.001214	0.001260
lo BS spread	-0.001044	-0.001134	-0.001518	-0.0003216	**-0.001633**	-0.0005408
62	0.000792	0.000916	0.000816	0.0007137	0.000758	0.0006822
hi inflation	-0.000473	0.001040	-0.000695	-7.467E-06	-0.0003605	-0.0006050
16	0.000933	0.001520	0.000992	0.0009608	0.0008412	0.001123
lo inflation	-0.001089	-0.0001742	-0.0007489	-0.0007833	-0.001106	-0.0006646
29	0.001372	0.001422	0.001327	0.001328	0.001528	0.001172
hi IP growth	-0.000878	-0.001439	-0.0007248	-0.001147	-0.001783	-0.0006036
22	0.001518	0.001480	0.001503	0.001430	0.001704	0.001340
lo IP growth	0.002023	0.003017	0.001567	0.003150	0.001965	0.002291
24	0.002187	0.002180	0.002223	0.002046	0.002713	0.001769
hi Cap.Util	**-0.001310**	**-0.001796**	**-0.002342**	**-0.001477**	**-0.002109**	**-0.001992**
46	0.000505	0.000894	0.0008686	0.0004804	0.0005724	0.0006857
lo Cap.Util	0.002214	0.002086	0.002438	0.001937	0.002261	0.002225
32	0.002041	0.002066	0.001999	0.002055	0.002513	0.001697
hi Dollar	-0.001312	-0.001675	-0.001708	-0.001458	-0.002373	-0.001080
21	0.001343	0.001490	0.001535	0.001295	0.001864	0.001315
lo Dollar	0.001110	-0.0001614	0.0003148	0.0008941	0.0006764	0.0002573
52	0.001210	0.001418	0.001295	0.001211	0.001412	0.001087
hi Corp. Iliq.	0.001939	-0.0009614	4.437E-05	0.001088	0.001056	-0.000401
22	0.001487	0.002032	0.002218	0.001464	0.001886	0.001637
lo Corp. Iliq.	0.000225	0.0004896	0.000355	0.000338	3.165E-05	0.000755
8	0.001159	0.001275	0.001047	0.001478	0.001189	0.001465
hi Stock Liq	0.0001127	-0.0008162	-0.0005099	1.491E-05	-0.0005191	-0.0005424
21	0.0009522	0.001181	0.001012	0.001109	0.0009659	0.001300
lo Stock Liq	-0.0007968	0.001047	-0.0007385	0.0008812	-0.0008808	0.0006012
22	0.001270	0.001366	0.001216	0.001104	0.001146	0.001170

table 5, page 3

fund grouping:	lag return high	lag return low	yield high	yield low	lag flow high	lag flow low
Uncond:	-0.0006268	0.0001378	-0.0004992	1.541E-05	-0.001425	-0.001177
168	0.0005424	0.0007610	0.0003925	0.0008509	0.0005681	0.000562
hi short rate	-0.0003681	**-0.005447**	**-0.005014**	-0.001841	0.0003037	**-0.003974**
3	0.001414	0.002214	0.001352	0.001760	0.001630	0.001129
lo short rate	-6.293E-05	-0.000535	-0.0001057	-0.0002523	-0.002462	-0.002024
64	0.001083	0.001427	0.0006638	0.001759	**0.001277**	0.001315
hi slope	-0.002013	-0.001239	-0.0004289	-0.005200	-0.0006703	-0.001773
17	0.003093	0.001320	0.0007106	0.003188	0.001465	0.001876
lo slope	-0.001135	0.0005442	-0.0002150	-0.0005787	-7.879E-05	-0.0001377
46	0.000758	0.0009145	0.0006863	0.0007086	0.0006943	0.0005882
hi convexity	-0.002179	-0.001271	-0.0007349	-0.002771	-0.0009922	-0.001428
15	0.003479	0.000972	0.0007412	0.003176	0.001388	0.002045
lo convexity	-0.001590	-0.001156	-0.001639	-0.001108	-0.001644	-0.001880
43	0.001097	0.001089	0.001024	0.001004	0.001182	0.001120
hi volatility	-0.001062	-0.000607	-0.001358	-0.000664	-0.000544	-0.000690
11	0.002281	0.001491	0.001365	0.001540	0.001554	0.001177
lo volatility	-0.000201	-0.0007568	-3.860E-05	-0.000561	-0.002194	-0.001699
62	0.001120	0.001340	0.0006092	0.001692	0.001184	0.001234
hi credit	**0.001978**	**0.009034**	**0.002713**	**0.008783**	0.001629	0.001763
14	0.000887	0.004207	0.001194	0.004128	0.0008930	0.000939
lo credit	-0.001401	-0.0006883	-0.0008111	-0.001418	**-0.001193**	**-0.001276**
78	0.000744	0.0006606	0.0004447	0.000752	0.0005932	0.000616
hi BS spread	-0.001912	-0.0008837	-0.001191	-0.001584	-0.001935	-0.001114
16	0.001969	0.0005311	0.001109	0.001354	0.001245	0.000985
lo BS spread	-0.000674	-0.001477	-0.0009357	-0.001348	**-0.002913**	**-0.002712**
62	0.001054	0.0008753	0.0006346	0.001191	0.001313	0.001321
hi inflation	0.001099	-0.000809	-0.001053	0.000929	0.001122	-0.000487
16	0.001158	0.001683	0.001026	0.001553	0.001375	0.000976
lo inflation	-0.000613	-0.001156	-0.001171	-0.000353	-0.001851	-0.002100
29	0.001149	0.002026	0.000838	0.002056	0.001849	0.001795

table 5, page 4

fund grouping:	lag return high	lag return low	yield high	yield low	lag flow high	lag flow low
hi IP growth	**-0.002423**	-0.0003311	-0.0002223	-0.002293	-0.001348	-0.001129
22	0.001163	0.002190	0.0009179	0.002451	0.0008949	0.0009214
lo IP growth	0.000326	0.003722	-0.0008296	0.004992	-0.001418	-0.002039
24	0.001808	0.003217	0.001672	0.003145	0.001948	0.001897
hi Cap.Util	**-0.001741**	-0.001108	**-0.001402**	**-0.002376**	-0.001220	**-0.001155**
46	0.000869	0.0007817	0.0005294	0.000917	0.000777	0.000541
lo Cap.Util	-1.280E-06	0.003585	0.000635	0.003386	0.0001420	-3.381E-06
32	0.001463	0.003058	0.001211	0.003389	0.0009886	0.0009944
hi Dollar	-0.002044	-0.001138	-0.001659	-0.001813	-0.001627	-0.001292
21	0.001815	0.001343	0.001619	0.001656	0.001392	0.001323
lo Dollar	-0.000537	0.001629	-3.584E-06	0.000848	-0.002157	-0.001465
52	0.001187	0.001796	0.0005821	0.002149	0.000991	0.000927
hi Corp Iliq.	0.001644	0.001783	0.0005855	0.0004965	0.0009585	0.001278
22	0.001746	0.002018	0.001097	0.002818	0.001316	0.001238
lo Corp Iliq.	0.0002381	0.0008307	5.504E-05	0.0006821	0.0005009	0.0003007
8	0.001025	0.002498	0.001033	0.001873	0.001178	0.001078
hi Stock Liq.	-0.0004052	-0.0001276	-0.0005798	-1.638E-05	-8.152E-05	0.0001110
21	0.001299	0.001483	0.001035	0.001342	0.001576	0.001472
lo Stock Liq.	-0.001128	0.0001310	-0.0007022	0.0007927	-0.001987	-0.002371
22	0.0009591	0.001760	0.001288	0.001298	0.002156	0.002066

Table 6

Fixed Income Fund Conditional Performance using Term Structure Models

Abnormal returns in excess of the Government-Corporate bond index are shown for equal-weighted portfolios of funds grouped on high versus low asset size, turnover and expense ratios. High-asset funds are those in the top third of all funds, while low asset funds are in the bottom third, etc. The alphas are decimal fractions per month, for the January, 1986 through December, 1999 period (168 observations), the lag flow group has twelve fewer observations and starts in January of 1987. Heteroskedasticity-consistent T-statistics are shown in parentheses. Tdiff is the t-ratio for the difference between the high and low-state alphas.

fund	asset		turnover		expense	
grouping:	high	low	high	low	high	low
State:						
One-factor Affine Model						
hi short rate	-0.00198	-0.000478	-0.0025	-0.00098	-0.00191	-0.00261
	(-12.1)	(-0.488)	(-29.3)	(-1.42)	(-7.23)	(-5.11)
lo short rate	2.27E-05	-0.000321	-0.000235	0.000249	-0.000377	0.000107
	(0.229)	(-0.301)	(-0.231)	(0.248)	(-0.338)	(0.118)
Tdiff	-2.00	-0.108	-2.23	-1.01	-1.34	-2.61
Two-factor Affine Model						
hi short rate	-0.00139	-0.000432	-0.00142	-0.000503	-0.00128	-0.000903
	(-2.37)	(-0.562)	(-2.69)	(-0.856)	(-2.60)	(-1.92)
lo short rate	0.000316	-0.00101	-0.00101	0.000517	-0.000594	-0.000189
	(0.316)	(-0.456)	(-0.357)	(0.467)	(-0.386)	(-0.123)
Tdiff	-1.40	0.246	-0.155	-0.809	-0.459	-0.460
hi slope	-0.000204	-0.00104	-0.00158	-0.000187	-0.00108	-0.000948
	(-0.104)	(-0.181)	(-0.175)	(-0.0969)	(-0.283)	(-0.211)
lo slope	-7.14E-05	9.97E-05	-0.000157	-8.59E-05	-0.000358	-0.000169
	(-0.055)	(0.145)	(-0.227)	(-0.0618)	(-0.253)	(-0.119)
Tdiff	-0.0461	-0.185	-0.167	-0.0347	-0.257	-0.239

table 6, page 2

fund grouping:	lag return high	lag return low	yield high	yield low	lag flow high	lag flow low
One-factor Affine Model						
hi short rate	-0.000492	-0.00262	-0.00273	-0.000888	-0.000139	-0.00212
	(-0.517)	(-7.62)	(-8.47)	(-0.626)	(-0.130)	(-13.5)
lo short rate	-0.000298	-0.000184	-0.000263	-0.000124	-0.000372	4.05E-05
	(-0.285)	(-0.137)	(-0.645)	(-0.0723)	(-0.524)	(0.0579)
Tdiff	-0.138	-1.76	-4.74	-0.343	0.181	-3.01
Two-factor Affine Model						
hi short rate	-0.000853	-0.000874	-0.00265	8.94E-06	-0.000450	-0.00191
	(-1.26)	(-2.19)	(-6.10)	(0.00677)	(-0.621)	(-7.28)
lo short rate	-0.000115	-1.13E-05	0.000159	-0.000792	-0.000342	0.000908
	(-0.0932)	(-0.0085)	(0.330)	(-0.287)	(-0.388)	(0.942)
Tdiff	-0.540	-0.620	-4.41	0.253	-0.104	-2.60
hi slope	-0.000673	0.000138	-0.000478	-0.00142	-0.000611	-0.0010
	(-0.229)	(0.0436)	(-0.713)	(-0.209)	(-0.432)	(-0.564)
lo slope	-0.000746	0.000293	-0.000325	-0.000239	-0.000295	-0.000183
	(-0.677)	(0.253)	(-0.719)	(-0.0958)	(-0.209)	(-0.520)
Tdiff	0.0229	-0.0383	-0.192	-0.242	-0.209	-0.453

Table 7

Fixed Income Fund Conditional Performance: Models with Extra Factors

Abnormal returns in excess of the Government-Corporate bond index are shown for equal-weighted portfolios of funds grouped on various high versus characteristics. High-asset funds are those in the top third of all funds, while low asset funds are in the bottom third, etc. The models are the extended affine models with one additional factor. The additional factor corresponds to the state of the economy being examained, as explained in the text. The instruments are a constant and dummy variables for high or low values of the spot rate, term structure slope and the additional state variable. The alphas are decimal fractions per month, for the January, 1986 through December, 1999 period (168 observations), results for funds grouped by lagged flow have start in 1987 and have twelve fewer observations. Heteroskedasticity-consistent T-statistics are shown in parentheses. Tdiff is the t-ratio for the difference between the conditional alphas in the high and low economic states.

fund	asset		turnover		expense	
grouping:	high	low	high	low	high	low
hi convexity	-0.000786	-0.000580	-0.000137	-0.000730	-0.00126	-0.000156
	(-0.355)	(-0.384)	(-0.0986)	(-0.337)	(-0.464)	(-0.138)
lo convexity	-0.000725	-0.000911	-0.000785	-0.000498	-0.00127	-0.000620
	(-1.13)	(-1.00)	(-1.15)	(-0.782)	(-1.42)	(-1.07)
Tdiff	-0.0276	0.177	0.428	-0.102	0.00565	0.374
hi volatility	-0.000418	-0.000355	6.07E-05	0.000375	-0.00809	-0.00534
	(-0.667)	(-0.480)	(0.098)	(0.570)	(-1.08)	(-0.841)
lo volatility	-4.05E-05	-0.000549	0.000459	0.000673	-0.000364	-1.06E-05
	(-0.042)	(-0.574)	(0.604)	(0.677)	(-0.002)	(-0.013)
Tdiff	-0.325	0.161	-0.409	-0.247	-0.335	-0.507
hi credit	0.00349	0.00340	0.00249	0.00309	0.00313	0.00276
	(1.19)	(1.14)	(1.08)	(1.18)	(1.04)	(1.33)
lo credit	0.000362	0.000158	-0.00059	-0.000565	-0.000773	-0.000547
	(0.598)	(0.336)	(-1.84)	(-1.42)	(-1.68)	(-1.88)
Tdiff	1.00	1.07	1.32	1.37	1.28	1.57
hi BS spread	-3.08E-05	-0.000297	-0.000564	0.000179		
	(-0.0480)	(-0.392)	(-0.537)	(0.380)		
lo BS spread	-0.00055	-0.00059	-0.00114	-3.20E-05		
	(-0.707)	(-0.506)	(-1.21)	(-0.039)		
Tdiff	0.505	0.234	0.428	0.219		

table 7, page 2

fund grouping:	asset high	asset low	turnover high	turnover low	expense high	expense low
hi Cap.Util	-0.000132	0.000615			-0.00157	-0.00111
	(-0.175)	(-0.475)			(-3.30)	(-2.34)
lo Cap.Util	-0.000604	-0.00071			0.00167	0.00175
					(0.744)	(1.17)
Tdiff	0.431	0.743			-1.41	-1.81
hi Dollar	-0.000377	-0.000631	-0.000638	-0.000519	-0.00127	-2.50E-05
	(-0.526)	(-0.795)	(-0.777)	(-0.798)	(-1.07)	(-0.049)
lo Dollar	0.00132	-0.000360	0.000644	0.000960	0.000878	0.000468
	(1.21)	(-0.280)	(0.546)	(0.866)	(0.666)	(0.470)
Tdiff	-1.30	-0.180	-0.892	-1.15	-1.21	-0.441

fund grouping:	lag return high	lag return low	yield high	yield low	lag flow high	lag flow low
hi convexity	-0.00177	-0.000289	-0.000591	-0.00131	-0.000763	-0.000842
	(-0.421)	(-0.689)	(-0.946)	(-0.439)	(-0.592)	(-0.436)
lo convexity	-0.00106	-0.000878	-0.000963	-0.000497	-0.000611	-0.000576
	(-1.03)	(-0.938)	(-1.33)	(-0.553)	(-0.739)	(-0.931)
Tdiff	-0.159	0.663	0.393	-0.259	-0.099	-0.130
hi volatility	-0.000726	-0.000220	-0.000894	-0.000264	-0.00049	-0.000465
	(-0.443)	(-0.207)	(-1.30)	(-0.293)	(-0.532)	(-0.718)
lo volatility	-0.000308	-0.000323	-0.000124	-0.000383	-0.000504	-1.96E-05
	(-0.277)	(-0.257)	(-0.286)	(-0.236)	(-0.730)	(-0.027)
Tdiff	-0.211	0.063	-0.944	0.064	0.013	-0.455
hi credit	0.000711	0.00467	0.00116	0.00488	0.000558	0.000753
	(0.783)	(1.12)	(0.986)	(1.09)	(0.810)	(0.781)
lo credit	-0.000969	-0.000206	-0.000603	-0.000639	-0.000640	-0.000539
	(-1.40)	(-0.0417)	(-1.87)	(-0.978)	(-1.56)	(-1.37)
Tdiff	1.46	1.16	1.44	1.23	1.50	1.36

fund grouping:	lag return high	lag return low	yield high	yield low	lag flow high	lag flow low
hi BS spread	0.000425	-0.000772	-0.000286	3.32E-05	-0.00121	-0.000680
	(0.363)	(-1.45)	(-0.330)	(0.0393)	(-2.11)	(-1.33)
lo BS spread	0.000208	-0.00136	-0.00106	-0.000170	-0.000611	-0.000308
	(0.143)	(-1.20)	(-1.26)	(-0.115)	(-0.852)	(-0.442)
Tdiff	0.110	0.538	0.759	0.121	-0.632	-0.430
hi Cap.Util			-0.00106	-0.00184	-0.000932	-0.000706
			(-2.57)	(-2.19)	(-1.32)	(-1.81)
lo Cap.Util			0.000521	0.00245	-0.000182	-0.000128
			(0.558)	(0.815)	(-0.253)	(-0.161)
Tdiff			-1.55	-1.37	-0.735	-0.650
hi Dollar	-0.000888	-0.000276	-0.000664	-0.000649	-0.00103	-0.000735
	(-0.785)	(-0.324)	(-0.666)	(-0.726)	(-1.41)	(-0.924)
lo Dollar	-0.000314	0.00134	8.66E-05	0.000941	-0.000978	-0.000389
	(-0.264)	(0.823)	(0.178)	(0.483)	(-1.26)	(-0.607)
Tdiff	-0.353	-0.877	-0.676	-0.743	-0.045	-0.339

Table 8

Fixed Income Fund Returns in Excess of Style Benchmarks

Returns in excess of style indexes are shown for equal-weighted portfolios of funds grouped by style. The excess returns are decimal fractions per month, for various subperiods ending in December, 1999 (180 or fewer observations). The first group of three rows reports the unconditional sample means and standard deviations of the mean excess returns, followed by the number of months available. Subsequent rows report the same statistics conditional on various economic states, as measured by dummy variables. Figures larger than two standard errors of the mean are in bold.

fund style:	government	all	load	no load	high quality	high yield	mortgage
State:							
Uncond.	-0.002607	-0.0006659	-0.0002210	-9.196E-05	**-0.0009400**	0.0008908	**-0.001456**
	0.001424	0.0006209	0.0005789	0.0004927	0.0004399	0.001536	0.0002716
	180.0	180.0	168.0	168.0	132.0	120.0	132.0
hi short rate	-0.01651	**-0.003843**	**-0.004949**	**-0.002220**	-0.004463	0.000	-0.002933
	0.008535	0.001075	0.001330	0.0009297	0.003648	0.000	0.003037
	3.000	3.000	3.000	3.000	3.000	0.000	3.000
lo short rate	-0.002491	-0.0002784	-0.0001301	-0.0001436	-0.0001000	**0.005369**	**-0.001131**
	0.002616	0.0008671	0.001074	0.0009671	0.0005456	0.002046	0.0003687
	74.00	74.00	64.00	64.00	38.00	38.00	38.00
hi slope	**-0.008091**	**-0.002466**	-0.002751	-0.001765	**-0.001944**	6.594E-05	**-0.002613**
	0.002592	0.001215	0.001958	0.001467	0.0008749	0.003334	0.0007099
	19.00	19.00	17.00	17.00	14.00	14.00	14.00
lo slope	-0.001622	-0.001083	-0.0002295	-0.0003159	-0.0005923	0.001565	**-0.001626**
	0.002407	0.001068	0.0007180	0.0005843	0.0009220	0.002807	0.0005232
	46.00	46.00	46.00	46.00	43.00	32.00	43.00
hi convexity	-0.002054	-0.001502	-0.001336	-0.001291	**-0.001493**	0.0009287	**-0.001931**
	0.002510	0.001231	0.001820	0.001555	0.0006260	0.002285	0.0005504
	16.00	16.00	15.00	15.00	14.00	14.00	14.00
lo convexity	-0.003121	-0.0008589	-0.001722	-0.0009038	-0.001562	-0.002369	**-0.001932**
	0.002833	0.001010	0.001098	0.0006428	0.001209	0.005094	0.0006480
	43.00	43.00	43.00	43.00	33.00	22.00	33.00

Table 8, page 2

fund style:	government	all	load	no load	high quality	high yield	mortgage
State:							
hi volatility	-0.002052	0.002226	-0.001268	-0.0006972	-0.001574	-0.0006444	-0.002315
	0.005885	0.002746	0.001434	0.001340	0.001962	0.004932	0.001492
	11.00	11.00	11.00	11.00	11.00	9.000	11.00
lo volatility	-0.001744	-0.0003042	-0.0001045	-0.0005426	-0.0004254	**0.004636**	**-0.001087**
	0.002448	0.0008481	0.001002	0.0009439	0.0004461	0.002114	0.0003523
	70.00	70.00	62.00	62.00	40.00	40.00	40.00
hi credit	**0.01054**	**0.006034**	**0.006144**	**0.005715**	**0.002582**	**0.009122**	**-0.001253**
	0.004198	0.002573	0.002715	0.002491	0.0009020	0.003942	0.0005326
	14.00	14.00	14.00	14.00	14.00	14.00	14.00
lo credit	**-0.005065**	**-0.001316**	-0.001099	**-0.001145**	**-0.001531**	0.0003204	**-0.001858**
	0.001832	0.0006586	0.0005548	0.0004559	0.0005506	0.001634	0.0004645
	83.00	83.00	78.00	78.00	68.00	56.00	68.00
hi BS spread	**-0.008426**	-0.001403	-0.001404	-0.001547	-0.002460	0.0004272	**-0.001455**
	0.004065	0.001157	0.001240	0.001068	0.001535	0.002997	0.0004843
	16.00	16.00	16.00	16.00	16.00	16.00	16.00
lo BS spread	-0.003187	**-0.001202**	-0.001301	-0.0008924	-0.0008702	0.0007325	**-0.001244**
	0.002613	0.0005276	0.0007473	0.000569	0.0005939	0.001929	0.0005815
	66.00	66.00	62.00	62.00	32.00	32.00	32.00
hi inflation	-0.006209	-0.002644	-0.0007968	0.000388	-0.0009813	-0.01079	-0.003346
	0.005762	0.002936	0.001017	0.000893	0.001950	0.009645	0.001349
	16.00	16.00	16.00	16.00	11.00	8.000	11.00
lo inflation	-0.004731	-0.001228	-0.001110	-0.000611	**-0.001539**	0.001773	**-0.001336**
	0.003838	0.001261	0.001390	0.001264	0.0006860	0.002586	0.0005378
	30.00	30.00	29.00	29.00	24.00	24.00	24.00
hi IP growth	-0.0004109	-0.001034	-0.001068	-0.001148	-0.0007877	0.002018	**-0.001955**
	0.002698	0.001519	0.001576	0.001482	0.001260	0.003462	0.0006996
	22.00	22.00	22.00	22.00	20.00	19.00	20.00

Table 8, page 3

fund style:	government	all	load	no load	high quality	high yield	mortgage
lo IP growth	0.002097	**0.003916**	0.001614	0.003003	-0.0006928	0.002908	-0.0008667
	0.004872	0.002327	0.002525	0.001874	0.001465	0.007393	0.0004809
	25.00	25.00	24.00	24.00	20.00	16.00	20.00
hi Cap.Util	**-0.004933**	**-0.001781**	**-0.002027**	**-0.001466**	**-0.002814**	-0.003631	**-0.003143**
	0.002442	0.0005025	0.0006440	0.000469	0.001045	0.002714	0.0008989
	46.00	46.00	46.00	46.00	28.00	21.00	28.00
lo Cap.Util	0.003248	0.002167	0.002271	0.002271	0.0005841	0.005472	**-0.0009207**
	0.003191	0.002155	0.002255	0.001998	0.0008365	0.003713	0.0003598
	32.00	32.00	32.00	32.00	32.00	32.00	32.00
hi Dollar	-0.004828	-0.001443	-0.002041	-0.001035	-0.001875	-0.001453	**-0.0009795**
	0.003719	0.001282	0.001817	0.001122	0.001521	0.004083	0.0003951
	28.00	28.00	21.00	21.00	21.00	21.00	21.00
lo Dollar	-0.0006032	-0.0006483	0.00073	0.000476	-0.001360	-0.002348	**-0.001327**
	0.002808	0.001613	0.001279	0.001200	0.0008173	0.004750	0.0005387
	52.00	52.00	52.00	52.00	23.00	23.00	23.00
hi Corp Iliq.	0.002079	0.0008359	0.001004	0.0006339	-0.001474	0.004039	-0.0008824
	0.003368	0.001517	0.001854	0.001414	0.001573	0.005296	0.0004834
	22.00	22.00	22.00	22.00	14.00	14.00	14.00
lo Corp Iliq.	-0.0003646	0.0004182	0.0002915	0.0005091	0.0002779	0.002592	-0.0006262
	0.005362	0.001301	0.001198	0.001375	0.001685	0.002097	0.002014
	8.000	8.000	8.000	8.000	8.000	8.000	8.000
hi Stock Liq.	-0.001629	-0.0001388	-0.0003374	-0.0003119	-0.001412	0.0005970	-0.001578
	0.004693	0.001215	0.001063	0.001040	0.001446	0.003193	0.0004949
	24.00	24.00	21.00	21.00	17.00	16.00	17.00
lo Stock Liq.	-0.002642	-0.0003146	-0.0005840	0.0003060	0.0004471	0.0009286	-0.001030
	0.004582	0.0009644	0.001152	0.0008062	0.001603	0.004007	0.001008
	22.00	22.00	22.00	22.00	16.00	15.00	16.00

Table 9

Fixed Income Fund Risk Ajusted Returns in Excess of Style Benchmarks

Risk-ajusted SDF alphas for returns in excess of style indexes are shown for equal-weighted portfolios of funds grouped by style. Asymptotic standard errors are on the second line. The units are decimal fractions per month, for various subperiods ending in December, 1999 (180 or fewer observations), with the number of observations in the high and low states shown below the standard errors. Figures larger than two standard errors are in bold.

fund style:	government	all	load	no load	high quality	high yield	mortgage
State:							
Panel A: One-factor Affine Model							
hi short rate	**-0.009274**	**-0.002197**	**-0.002562**	-0.001139	-0.002695	0.000	-0.002155
	0.002886	0.0003285	5.380E-05	0.0007026	0.001742	0.000	0.002408
	3.000	3.000	3.000	3.000	3.000	0.000	3.000
lo short rate	-0.002324	-0.0004258	-0.0001507	-0.0001086	-0.0004883	0.000	**-0.001282**
	0.001265	0.0008134	0.001001	0.0009514	0.0003291	0.000	0.0003516
	74.00	74.00	64.00	64.00	38.00	0.000	38.00
Panel B: Two-factor Brennan-Schwartz Model							
hi short rate	**-0.005075**	**-0.001459**	-0.0009529	-0.0003710	-0.001270	0.000	-0.001549
	0.0007636	0.0001371	0.0009940	0.0007155	0.001260	0.000	0.002497
	3.000	3.000	3.000	3.000	3.000	0.000	3.000
lo short rate	-0.0008610	-0.0004529	-0.0001043	5.854E-05	-0.0007459	0.000	**-0.001425**
	0.002301	0.002171	0.001217	0.001251	0.0004399	0.000	0.0003613
	74.00	74.00	64.00	64.00	38.00	0.000	38.00
hi slope	**-0.001983**	-0.0006831	-0.0009922	-0.0002242	-0.001076	0.0006196	**-0.001914**
	0.0008741	0.0009093	0.0005265	-0.0003876	0.000629		0.000540
	19.00	19.00	17.00	17.00	14.00	14.00	14.00
lo slope	-0.001047	-0.0005340	-0.0002284	-0.0002014	-0.0004080	0.001518	**-0.001771**
	0.003425	0.001504	0.005813	0.001569	0.001931	0.001115	0.0006683
	46.00	46.00	46.00	46.00	43.00	32.00	43.00

Table 9, page 2

Panel C: Two-factor Affine Model

fund style: / State:	**government**	**all**	**load**	**no load**	**high quality**	**high yield**	**mortgage**
hi short rate	**-0.005063**	**-0.001443**	**-0.001489**	-0.0004680	-0.0002917		**0.001696**
	0.0006846	0.0001184	0.0006546	0.0006172	0.0002024		0.0007333
	3.000	3.000	3.000	3.000	3.000	0.000	3.000
lo short rate	-0.0006925	-0.0006745	-0.0003879	-0.0001308	-0.0001483		**-0.001423**
	0.001509	0.001318	0.001630	0.0009820	0.0004777		0.000441
	74.00	74.00	64.00	64.00	38.00		38.00
hi slope	-0.001833	-0.000509	-0.001047	-0.0002991	**-0.001235**	-0.001227	**-0.001862**
	0.001037	0.001858	0.001724	0.0006335	0.0001478		0.0006075
	19.00	19.00	17.00	17.00	14.00	14.00	14.00
lo slope	-0.0008797	-0.0006049	-0.0001674	-0.0001472	-0.0001076	-0.0001076	**-0.001798**
	0.003563	0.0009018	0.006357	0.002144	0.009653	-0.0009162	0.0008568
	46.00	46.00	46.00	46.00	43.00	32.00	43.00

Panel D: Extended Two-factor Affine Model

fund style: / State:	**government**	**all**	**load**	**no load**	**high quality**	**high yield**	**mortgage**
hi convexity	-0.003133	-0.000499	-0.000238	-0.000171	**-0.001227**	0.001223	**-0.001732**
	0.001745	0.001156	0.002185	0.001897	0.0004005	0.002149	0.000568
	16.00	16.00	15.00	15.00	14.00	14.00	14.00
lo convexity	**-0.003138**	-0.0008786	-0.0007433	-0.0005465	-0.0008465	0.0003069	**-0.001711**
	0.001165	0.0009473	0.0009675	0.0006181	0.0007080	0.003622	0.000604
	43.00	43.00	43.00	43.00	33.00	22.00	33.00
hi volatility	-0.002341	-0.000287	-7.045E-05	0.0003977	-0.0004843	0.0009061	-0.001236
	0.003950	0.002608	0.0007317	0.0005908	0.0007153	0.002797	0.001159
	11.00	11.00	11.00	11.00	11.00	9.000	11.00
lo volatility	-0.002188	-0.0005823	0.0004015	-0.0001628	**-0.0007360**	0.001750	**-0.001380**
	0.001258	0.0008213	0.0009286	0.0008755	0.0003119	0.001790	0.000345
	70.00	70.00	62.00	62.00	40.00	40.00	40.00

Table 9, page 3

fund style:	**government**	**all**	**load**	**no load**	**high quality**	**high yield**	**mortgage**
State:							
hi credit	-0.005889	-0.002324	0.003819	0.003128	-0.008151	0.003009	**-0.001797**
	0.004717	0.003201	0.003088	0.002876	0.002142	0.006926	0.0006305
	14.00	14.00	14.00	14.00	14.00	14.00	14.00
lo credit	**-0.002554**	-0.0005991	0.0001907	2.203E-05	-0.0006820	0.000536	**-0.001314**
	0.000874	0.0005932	0.0005728	0.0004699	0.0004134	0.002623	0.0005088
	83.00	83.00	78.00	78.00	68.00	56.00	68.00
hi BS spread	**-0.001377**	-0.0005723	-0.001060	**-0.001144**	1.011E-05	0.007511	-0.0009876
	0.000344	0.0005845	0.0007692	0.000428	0.0005290	0.005991	0.0005598
	16.00	16.00	16.00	16.00	16.00	16.00	16.00
lo BS spread	**-0.003289**	-0.0006430	-0.0007760	-0.0007339	-0.0003275	0.001466	-0.0008469
	0.000744	0.0004419	0.0006693	0.0006215	0.0002952	0.002264	0.0006553
	66.00	66.00	62.00	62.00	32.00	32.00	32.00
hi inflation	-0.003338	-0.002151	-0.0004051	0.0003573	-0.001098	-0.006722	-0.001138
	0.003938	0.003224	0.0008425	0.0009201	0.0008575	0.006949	0.001316
	16.00	16.00	16.00	16.00	11.00	8.000	11.00
lo inflation	-0.001076	-0.0004645	7.030E-05	-0.0003273	-0.0008504	0.002421	**-0.001483**
	0.001892	0.001219	0.001319	0.001274	0.0003518	0.001990	0.0005145
	30.00	30.00	29.00	29.00	24.00	24.00	24.00
hi IP growth	-0.002505	-0.0006901	-0.000283	-0.000177	-0.0004229	0.001126	**-0.001812**
	0.002161	0.001471	0.001518	0.001466	0.0006885	0.003049	0.000746
	22.00	22.00	22.00	22.00	20.00	19.00	20.00
lo IP growth	-0.002370	-0.000563	-0.000210	5.616E-06	-0.001210	0.002136	-0.000365
	0.003848	0.002962	0.002976	0.002517	0.002297	0.005683	0.001040
	25.00	25.00	24.00	24.00	20.00	16.00	20.00
hi Cap. Util	**-0.002629**	-0.0006527	**-0.001317**	**-0.001279**	**-0.002456**	-0.001650	**-0.002922**
	0.000529	0.0003951	0.0004910	0.000421	0.000620	0.001994	0.000701
	46.00	46.00	46.00	46.00	28.00	21.00	28.00

Table 9, page 4

fund style:	**government**	**all**	**load**	**no load**	**high quality**	**high yield**	**mortgage**
State:							
lo Cap. Util	-0.002785	-0.0007619	0.001764	0.001698	**0.001236**	0.005241	**-0.0009018**
	0.003240	0.002519	0.002001	0.001779	0.000501	0.003190	0.0004019
	32.00	32.00	32.00	32.00	32.00	32.00	32.00
hi Dollar	**-0.001958**	-0.0004285	-0.000901	-0.0001243	-0.001059	0.0008441	**-0.0009396**
	0.000596	0.001741	0.001100	0.0004212	0.000502	0.003160	0.0004005
	28.00	28.00	21.00	21.00	21.00	21.00	21.00
lo Dollar	0.000874	-0.000396	0.000991	0.000396	-0.0009460	0.000852	**-0.001416**
	0.002133	0.002368	0.001179	0.001087	0.0006621	0.004410	0.000577
	52.00	52.00	52.00	52.00	23.00	23.00	23.00
hi Corp ILiq.	-0.002317	-0.0004975	-0.000189	-0.001406	-0.0008085	0.004059	**-0.001001**
	0.001961	0.001335	0.002860	0.000981	0.0008061	0.004446	0.000468
	22.00	22.00	22.00	22.00	14.00	14.00	14.00
lo Corp ILiq.	**-0.002884**	-0.0006123	0.0003389	0.0002371	0.0003198	0.001961	-0.0005783
	0.000849	0.0006881	0.0007441	0.0004257	0.0007601	0.001924	0.001682
	8.000	8.000	8.000	8.000	8.000	8.000	8.000
hi Stock Liq.	**0.01482**	0.0002165	6.279E-05	1.382E-05	-0.0003520	0.001565	**-0.001547**
	0.003832	0.0004293	0.0007297	0.0008971	0.0004994	0.001802	0.0004862
	24.00	24.00	21.00	21.00	17.00	16.00	17.00
lo Stock Liq.	-0.001493	-0.002462	-0.0001750	0.0003469	0.001218	0.001527	-0.0008159
	0.002154	0.001660	0.0007015	0.0007010	0.0008206	0.002992	0.0008587
	22.00	22.00	22.00	22.00	16.00	15.00	16.00