

Measuring the Timing Ability of Fixed Income Mutual Funds

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ABSTRACT

Measuring the Timing Ability of Fixed Income Mutual Funds

This paper evaluates the ability of bond funds to "market time" factors related to bond markets. Timing ability generates nonlinearity in fund returns, but there are several non-timing-related sources of nonlinearity. We find that controlling for non-timing-related nonlinearity is important. Funds' returns are more concave than benchmark returns, relative to nine common factors, and this would appear as poor timing ability in naive models. With the controls, the overall distribution of the timing coefficients appears neutral to weakly positive. The timing-adjusted performance of many bond funds appears significantly negative on an after-cost basis, but many funds have positive performance on a before-cost basis.

1. Introduction

The amount of academic research on bond fund performance is small in comparison to the economic importance of bond funds. Recently the total net assets of U.S. bond funds has been about 1/6 the amount in equity-style mutual funds and similar to the value of hedge funds. Large amounts of additional fixed-income assets are held in professionally managed portfolios outside of mutual funds, for example in pension funds, trusts and insurance company accounts. The turnover of a typical bond mutual fund far exceeds that of a typical equity fund (e.g. Moneta, 2008), suggesting that active portfolio management is important in bond funds. Thus, it is important to understand the performance of bond fund managers.

Elton, Gruber and Blake (EGB, 1993, 1995) and Ferson, Henry and Kisgen (2006) study US bond mutual fund performance, concentrating on the funds' risk-adjusted returns, or alphas. They find that the typical risk-adjusted, average performance is slightly negative after costs, and largely driven by funds' expenses. This might suggest that investors would be better off selecting low-cost passive funds, and EGB draw that conclusion. However, performance may be decomposed into components, such as timing and selectivity ability. If investors place value on timing ability, for example a fund that can mitigate losses in down markets, they would be willing to pay for this insurance with lower average returns. This is one of the first papers to comprehensively study the ability of US bond funds to time their markets.¹

Timing ability on the part of a fund manager is the ability to use superior information about the future realizations of common factors that affect bond market returns.² Selectivity refers to the use of security-specific information. If common factors explain a significant part of the variance of bond returns, a significant fraction of the potential performance of bond funds might be attributed to timing. However, measuring the timing ability

¹ Brown and Marshall (2001) develop an active style model and an attribution model for fixed

² We do not explicitly study "market timing" in the sense recently taken to mean trading by investors in a fund to exploit stale prices reflected in the fund's net asset values. But we will see that these issues can affect measures of a fund manager's ability.

of bond funds is a subtle problem.

Traditional models of market timing ability rely on convexity in the relation between the fund's returns and the common factors.³ In bond funds, perhaps even more clearly than in equity funds, convexity or concavity can arise for various reasons unrelated to timing ability. We find that other sources of nonlinearity are important, and our empirical analysis attempts to control for other sources of nonlinearity.

We find that funds' returns are typically more concave, in relation to a set of nine bond market factors, than are unmanaged benchmarks. Thus, funds would appear to have poor (negative) market timing ability in naive models. When we introduce controls for non-timing-related nonlinearities the overall distribution of the timing coefficients appears neutral to weakly positive. After adjusting for timing ability the performance of many bond funds is significantly negative on an after-cost basis but many funds have significant positive performance on a before cost basis.

The rest of the paper is organized as follows. Section 2 describes the models and methods. Section 3 describes the data. Section 4 presents our empirical results and Section 5 offers some concluding remarks.

2. Models and Methods

A traditional view of performance separates timing ability from security selection ability, or selectivity. Timing is closely related to asset allocation, where funds rebalance the portfolio among asset classes and cash. Selectivity essentially means picking good securities within the asset

³ The alternative approach is to directly examine managers' portfolio weights and trading decisions to see if they can predict returns and factors (e.g. Grinblatt and Titman, 1989). Comer (2006), Moneta (2008) and Wang (2007) are early steps in this direction for bond funds. Of course, weight-based approaches cannot capture market timing that occurs between weight reporting intervals, which can be up to six months in length.

classes.

Like equity funds, bond funds engage in activities that may be viewed as selectivity or timing. Bond funds may attempt to predict issue-specific supply and demand or changes in credit risks associated with particular bond issues. Funds can also attempt to exploit liquidity differences across individual bonds. These trading activities can be classified as security selection. In addition, managers may tune the interest rate sensitivity (e.g., duration) of the portfolio to time changes in interest rates in anticipation of economic developments. They may vary the allocation to asset classes differing in credit risk or liquidity, and tune the portfolio's exposure to economic factors. Since these activities relate to anticipating market-wide factors, they may naturally be considered as market timing.

Classical models of market-timing use the convexity in the relation between the fund's return and the "market" return to indicate timing ability. In these models the manager observes a private signal about the future performance of the market and adjusts the market exposure of the portfolio. If the response is assumed to be a linear function of the signal as modelled by Admati, Bhattacharya, Ross and Pfleiderer (1986), the portfolio return is a convex quadratic function of the market return as in the regression model of Treynor and Mazuy (1966). If the manager shifts the portfolio weights discretely, as modelled by Merton and Henriksson (1981), the convexity may be modelled with call options. We modify the classical setup for bond market factors and to control for nonlinearities that are unrelated to managers' timing ability.

2.1 Nonlinearity Unrelated to Timing

There are many reasons apart from timing ability that a fund's return could have a nonlinear relation to a market factor. We group these reasons into four general categories. This section explains the intuition for each effect.

First, the underlying assets held by a fund may have a nonlinear relation to market

factors. While nonlinearity may occur in equities, it is very likely in bonds. Even simple bond returns are nonlinearly related to interest rate changes, for example. Callable and convertible bonds contain explicit option components which are nonlinearly related to the underlying factors. As we show in Table 3 below, unmanaged bond benchmark returns are often convex functions of common factors. Thus, to measure timing ability it is important to control for this nonlinearity.

A second, related cause of nonlinearity is "interim trading," studied by Goetzmann, Ingersoll and Ivkovic (2000), Ferson and Khang (2002) and Ferson, Henry and Kisgen (2006). This refers to a situation where fund managers trade more frequently than the fund's returns are measured. With mutual funds interim trading definitely occurs. A related effect is derivatives or other securities with option-like payoffs. For example, a fund that holds call options bears a convex relation to the underlying asset (Jagannathan and Korajczyk, 1986). Derivatives may often be replicated by high frequency trading, so if we can control for interim trading we also control for these derivatives.⁴ Thus, controls for interim trading should also help control for nonlinearity in the options and option-like securities held by bond funds.

A third potential reason for nonlinearity unrelated to timing ability is stale pricing of a fund's assets. Thin or nonsynchronous trading has long been known to bias downward the estimates of beta for a portfolio (e.g., Fisher (1966), Scholes and Williams, 1977). If the degree of stale pricing is related to a market factor, we show below that such "systematic" stale pricing can create spurious concavity or convexity in the measured return.

Systematic stale pricing can be illustrated with another example using monthly returns on the Government Index, R_g , for 1989-2003. The measured return on a hypothetical fund is $R_{pt} = (1-\theta_t)R_{gt} + \theta_t R_{gt-1}$, where $\theta_t \in [0,1]$ captures the extent of stale pricing. We set $E(\theta_t)=0.15$,

⁴ Brown et al. (2004) explore arguments that incentives and behavioral biases can induce managers without superior information to engage in option-like trading within performance measurement periods.

which roughly says that 15% of the measured prices are stale. The stale pricing is systematic, or correlated with the return of the index: $\theta_t = 0.15 + b_1[R_{gt} - E(R_g)]$. We set b_1 so that the minimum value of θ_t is zero, implying $b_1 = -2.71$. Thus, prices become more stale when the index return is low. The Scholes and Williams effect says that the fund's measured beta on the index will be biased toward zero, to a greater extent when the pricing is more stale. Thus, the measured betas will be too low when the index return is low. This creates a spurious impression of market timing ability. Regressing the 177 monthly measured excess returns on the government index excess return and its square, the coefficient on the squared term is 0.23 and its t-ratio is 2.00. Thus, a fund with systematic stale pricing can appear to have timing ability if we fail to control for the stale pricing effect.

A fourth reason for nonlinearity unrelated to timing ability arises if there is public information about future asset returns. As shown by Ferson and Schadt (1996), even if the conditional relation between the fund and a benchmark return is linear, the conditional portfolio betas may be correlated with market returns because of their common dependence on public information, and the unconditional relation may be nonlinear. Examples of public information effects on equity fund timing coefficients are provided by Ferson and Warther (1996), Becker, et al (1999), Christopherson, Ferson and Turner (1999) and Ferson and Qian (2004).

In summary, in order to measure the market timing ability of bond funds we need to control for nonlinearity in the benchmark assets and for nonlinearity that may arise from interim trading, public information effects and systematic stale pricing. In the following subsections we modify the classical market timing model to allow for nonlinearity in the benchmark returns and develop controls for interim trading, public information effects and systematic stale pricing.

2.2 Classical Market Timing Models

The classical market-timing regression of Treynor and Mazuy (1966) is:

$$r_{pt} = a_p + b_p f_t + \lambda_p f_t^2 + u_{pt} \quad (1)$$

where r_{pt} is the fund's portfolio return, measured in excess of a short-term Treasury bill. With equity market timing, as considered by Treynor and Mazuy, f_t is the excess return of the stock market index. Treynor and Mazuy (1966) argue that $\lambda_p > 0$ indicates market-timing ability. The logic is that when the market is up, the successful market-timing fund will be up by a disproportionate amount. When the market is down, the fund will be down by a lesser amount. Therefore, the fund's return bears a convex relation to the market factor.

It seems natural to replace the equity market excess return with changes in systematic factors in bond markets, like interest rate levels and spreads. However, if a factor is not an excess return, the appropriate sign for the timing coefficient might not be obvious. For example, bond returns move in the opposite direction as interest rates, so a signal that interest rates are about to rise means bond returns are likely to be low. We show in the Appendix that market timing ability still implies a positive coefficient on the squared factor.

Stylized market-timing models confine the fund to a single risky-asset portfolio and cash. This makes sense theoretically, from the perspective of the Capital Asset Pricing Model (CAPM, Sharpe, 1964). Under that model's assumptions there is two-fund separation and all investors hold the market portfolio and cash. But two-fund separation is generally limited to single-factor term structure models, and there is no central role for a "market portfolio" of bonds in most fixed income models. In practice, however, bond funds often manage to a "benchmark" portfolio that defines the peer group or investment style. We use style-specific benchmarks to replace the market portfolio.

2.3 Addressing Nonlinearity in Benchmark Assets

We model nonlinearity in the relation between the benchmark asset returns and the common factors with a nonlinear regression:

$$r_{Bt} = a_B + b_B(f_t) + u_{Bt}, \quad (2)$$

where $b_B(f)$ is a nonlinear function of the factor changes. The Appendix derives the generalization of the market-timing regression that incorporates the nonlinear benchmark:

$$r_{pt} = a_p + b_p [b_B(f_t)] + \Lambda_p f_t^2 + u_{pt} \quad (3)$$

The intuition of Equation (3) is that the nonlinearity of the benchmark return determines the nonlinearity of the fund's return. If there is no market-timing ability ($\Lambda_p=0$) the nonlinearity of the fund's return mirrors that of the benchmark through the second term of the regression. A successful timer's return has a more convex relation than the benchmark, and thus $\Lambda_p > 0$. We combine equations (2) and (3), and estimate the model by the Generalized Method of Moments (Hansen, 1982).

One of the forms for $b_B(f)$ that we consider is a quadratic function, which has an interesting interpretation in terms of systematic coskewness. Asset-pricing models featuring systematic coskewness are studied, for example, by Kraus and Litzenberger (1976). Equation (1) is, in fact, equivalent to the quadratic "characteristic line" used by Kraus and Litzenberger. Under their interpretation the coefficient on the squared factor changes does not measure market timing, but measures the systematic coskewness risk. Thus, a fund's return can bear a convex relation to a factor because it holds assets with coskewness risk. Equations (2) and (3) allow the benchmark to have coskewness risk.

2.4 Addressing Interim Trading

Interim trading means that fund managers trade more frequently than the fund's returns are measured. This can lead to incorrect inferences about market timing ability, as shown by Jiang, Yao and Yu (2005) and to incorrect inferences about total performance, as shown by Ferson and Khang (2002). Ferson, Henry and Kisgen (2006) propose a solution using a continuous-time asset pricing model, where the time-aggregated model prices all portfolio strategies that may trade within the period as nonanticipating functions of the state variables in the model. Thus, a manager with no ability will not record abnormal performance. If the manager wastes resources by interim trading that generates trading costs, the portfolio return will be low and this should be detected as negative average performance. If the continuous-time model can price derivatives by replication with dynamic strategies, the use of derivatives is also covered by this approach.

Ferson, Henry and Kisgen show that the time-aggregated stochastic discount factor (SDF) from a set of popular term structure models is:⁵

$${}_{t-1}m_t = \exp(a - A_t^r + b'A_t^x + c'[x(t) - x(t-1)]). \quad (4)$$

In Equation (4) $x(t)$ is the vector of state variables in the model at time t . The terms $A_t^x = \sum_{i=1, \dots, 1/\Delta} x(t-1+(i-1)\Delta)\Delta$ approximate the integrated levels of the state variables over the period from $t-1$ to t . The monthly measurement period is divided into $(1/\Delta)$ intervals of length Δ —one trading day. A_t^r is the time-averaged level of the short-term interest rate. The empirical "factors," f_t , in the SDF thus include the usual discrete monthly changes in the state variables, but also include their

⁵ A stochastic discount factor is a random variable, ${}_{t-1}m_t$, that "prices" assets through the equation $E_{t-1}\{{}_{t-1}m_t(1+R_t)\}=1$.

time averages and the time-averaged short term interest rate: $f_t = \{[x(t) - x(t-1)], A_t^x, A_t^r\}$.

With the approximation $e^f \approx 1+f$, which is accurate for numerically small f , the SDF is linear in the expanded set of empirical factors. Since a linear SDF is equivalent to a beta pricing model, this motivates including the time-averaged variables $\{A_t^x, A_t^r\}$ as additional "factors" in the regression to control for interim trading. That is the approach we take in this paper.

2.5 Addressing Public Information

Conditional timing models control for public information effects by allowing funds' betas to vary over time with public information. Ferson and Schadt (1996) and Becker, et al. (1999) find that conditional timing models for equity funds are better specified than models that do not control for public information. In particular, Ferson and Schadt (1996) propose a conditional version of the market timing model of Treynor and Mazuy (1966):⁶

$$r_{pt} = a_p + b_p f_t + C_p'(Z_{t-1} f_t) + \lambda_p f_t^2 + u_t \quad (5)$$

where the interaction term $C_p'(Z_{t-1} f_t)$ controls for nonlinearity due to the public information, Z_{t-1} . We include similar interaction terms in this paper to control for public information effects.

2.6 Addressing Stale Prices

Thin or nonsynchronous trading in a portfolio biases estimates of the portfolio beta (e.g., Scholes and Williams, 1977), and a similar effect occurs when the measured value of a fund

⁶ Ferson and Schadt (1996) also derive a conditional version of the market timing model of Merton and Henriksson (1981), which views successful market timing as analogous to producing cheap call options. This model is considerably more complex than the conditional Treynor-Mazuy model, but they find that it produces similar results.

reflects stale prices, possibly due to illiquid assets (e.g. Getmansky, Lo and Makarov, 2004). If the extent of stale pricing is related to a common factor we call it *systematic stale pricing*. To address systematic stale pricing we use a simple model generalizing Getmansky, Lo and Makarov. Let r_{pt} be the true return on a fund's assets. The true return would be the observed return if no prices were stale. We assume r_{pt} is independent over time with mean μ . The measured return on the fund, r_{pt}^* , is given by:

$$r_{pt}^* = \theta_t r_{pt-1} + (1-\theta_t)r_{pt} \quad (6)$$

where the coefficient $\theta_t \in [0,1]$ measures the extent of stale pricing at time t . Getmansky, Lo and Makarov allow $K > 1$ lagged returns in Equation (6) to capture longer term smoothing in hedge fund returns, but they assume that the smoothing coefficients, θ_t , are constant over time. Our model allows time-varying smoothing coefficients in order to capture systematic stale pricing, but we restrict to a single lag. With K lags, the measured returns have a K -th order moving average structure. In our bond fund portfolio returns we find significant first order autocorrelations, but the second order autocorrelations are insignificant, suggesting a first-order moving average structure.

Assume that the factor change f_t has mean μ_f and variance σ_f^2 , is independent and identically distributed over time and is measured without error.⁷ To model systematic stale pricing consider a regression of θ_t on the factor changes:

⁷ While this modelling assumption is certainly false, it might be a reasonable approximation for a highly-traded Treasury index or the Lehman bond index data. Lehman's pricing staff employs a daily matrix pricing approach based on traders' daily quotes and bond characteristics, and they market several products that focus on providing timely prices to clients (see Lehman Brothers, 2006). In further support of this assumption, the autocorrelations of the factor changes and the benchmark returns in tables 1 and 2 are typically smaller than the autocorrelations of the fund portfolio returns in Table 1.

$$\theta_t = \delta_0 + \delta_1(f_t - \mu_f) + \varepsilon_t \quad (7)$$

where we assume that ε_t is independent of the other variables in the model. We are interested in moments of the true return like $\text{Cov}(r_{pt}, f_t^2)$, which measures the timing ability. Straightforward calculations relate the moments of the observable variables to the moments of the unobserved variables, as follows.

$$E(f^*) = \mu \quad (8a)$$

$$\text{Cov}(r_{pt}^*, f_t) = \text{Cov}(r_p, f)(1 - \delta_0 + 2\delta_1\mu_f) - \delta_1 \{\mu \sigma_f^2 + \text{Cov}(r_p, f^2)\} \quad (8b)$$

$$\begin{aligned} \text{Cov}(r_{pt}^*, f_t^2) &= \text{Cov}(r_p, f^2)(1 - \delta_0 + \delta_1\mu_f) \\ &\quad - \delta_1 \{ \mu E(f^3) + \text{Cov}(r_p, f^3) - [\text{Cov}(r_p, f) + \mu\mu_f](\mu_f^2 + \sigma_f^2) \} \end{aligned} \quad (8c)$$

$$\text{Cov}(r_{pt}^*, f_t) + \text{Cov}(r_{pt}^*, f_{t-1}) = \text{Cov}(r_p, f) \quad (8d)$$

$$\text{Cov}(r_{pt}^*, f_t^2) + \text{Cov}(r_{pt}^*, f_{t-1}^2) = \text{Cov}(r_p, f^2) \quad (8e)$$

$$\text{Cov}(r_{pt}^*, f_t^3) + \text{Cov}(r_{pt}^*, f_{t-1}^3) = \text{Cov}(r_p, f^3) \quad (8f)$$

Equation (8a) shows that stale prices will not affect the measured average returns in this model.⁸ Thus, for example we can examine funds' average returns net of a benchmark to measure average performance, and we do so below. Equation (8b) captures the bias in the measured covariance with the market. The market beta is proportional to this covariance. Equation (8c) shows the

⁸ Qian (2006) studies the effects of stale prices on the measured average performance of equity style funds, and finds that if staleness is correlated with new money flows there can be effects on average returns. See also Zeitowitz (2003) and Edelin (1999). Under reasonable assumptions bounding the magnitudes of flows, however, we can show that a model with flows produces the same reduced-form implications for the measurement of market timing as the model presented here.

measured covariance with the squared market return. When stale pricing is systematic ($\delta_1 \neq 0$) the true beta contaminates the measured timing ability and timing ability contaminates the measured beta.

Fortunately, equation (8e) reveals a simple way to control for a biased timing coefficients due to systematically stale prices. The sum of the covariances of the measured return with the squared factor changes and the lagged squared factor changes delivers the correct timing coefficient. This is similar to the bias correction for betas in the models of Scholes and Williams (1977), as revealed in Equation (8d).

2.7 Combining the Effects

In summary, the general form of the model is a system including Equation (2) and Equation (9):

$$r_{pt}^* = a + \beta' X_t + \lambda_p [f_t^2 + f_{t-1}^2] + u_{pt} \quad (9)$$

where X_t is a vector of control variables observed at t or before. The nonlinear function $b_B(f_t)$ is included in X_t to control for nonlinearity in the underlying benchmark assets. The time-averaged factor and short-term interest rate, $\{A^f, A^r\}$, control for interim trading. The products of the factors with lagged state variables control for public information effects. Lagged values of the factor changes, f_{t-1} , are included in X_t and in the timing term of (9) to control for systematic stale pricing.

3. The Data

We first describe our sample of bond funds. We then describe the interest rate and other economic data that we use to construct the factors relative to which we study timing ability.

Finally, we describe the funds' style-related benchmark returns.

3.1 Bond Funds

The mutual fund data are from the Center for Research in Security Prices (CRSP) mutual fund data base, and include returns for the period from January of 1962 through December of 2007. We select open-end funds whose stated objectives indicate that they are bond funds.⁹ We exclude money market funds and municipal securities funds. We subject the fund data to a number of screens as described in the Appendix. We group the funds into equally-weighted portfolios according to eight mutually exclusive investment styles: Index, Global, Short-term, Government, Mortgage, Corporate, High Yield and Other.¹⁰ We also form subgroups according to various fund characteristics, measured at the end of the previous year. Since the characteristics are likely to be associated with fund style, we form characteristic groups within each of the style classifications. The characteristics include fund age, total net assets, percentage

⁹ Prior to 1990 we consider funds whose POLICY code is B&P, Bonds, Flex, GS or I-S or whose OBJ codes are I, I-S, I-G-S, I-S-G, S, S-G-I or S-I. We screen out funds during this period that have holdings in bonds plus cash less than 70% at the end of the previous year. In 1990 and 1991 only the three digit OBJ codes are available. We take funds whose OBJ is CBD, CHY, GOV, MTG or IFL. If the OBJ code is other than GOV, we delete those funds with holdings in bonds plus cash totalling less than 70%. After 1991 we select funds whose OBJ is CBD, CHY, GOV, MTG, or IFL or whose ICDI_OBJ is BQ, BY, GM or GS, or whose SI_OBJ is BGG, BGN, BGS, CGN, CHQ, CHY, CIM, CMQ, CPR, CSI, CSM, GBS, GGN, GIM, GMA, GMB, GSM or IMX. From this group we delete 116 fund years for which the POLICY code is IG or CS.

¹⁰ Global funds are coded SI_OBJ=BGG or BGN. Short-term funds are coded SI_OBJ=CSM, CPR, BGS, GMA, GMS, GBS or GSM. Government funds are coded OBJ=GS POLICY=GOV, ICDI_OBJ=GS, or SI_OBJ=GIM or GGN. Mortgage funds are coded ICDI_OBJ=GM, OBJ=MTG or SI_OBJ=GMB. Corporate funds are coded as OBJ=CBD, ICDI_OBJ=BQ, POLICY=B&P or SI_OBJ=CHQ, CIM, CGN or CMQ. High Yield funds are coded as ICDI_OBJ=BY, SI_OBJ=CHY or OBJ=CHY or OBJ=I-G and Policy=Bonds. Index funds are identified by searching for the word "index" in the fund name. Other funds are defined as funds that we classify as bond funds (see the previous footnote), but which meet none of the above criteria.

cash holdings, percentage of holdings in options, reported income yield, turnover, load charges, expense ratios, the average maturity of the funds' holdings, and the lagged return for the previous year. The Appendix provides the details.

Summary statistics for the broad style-grouped funds' returns are reported in Panel A of Table 1. The mean returns are between 0.37 and 0.74% per month. The standard deviations of return range between 0.46% and 1.85% per month. The first-order autocorrelations range from 14% for Index funds to 30% for Short Term funds. The minimum return across all of the style groups in any month is -7.3%, suffered in October of 1979 by the Corporate bond funds. The maximum return is almost 11%, also earned by the Corporate funds, in November of 1981.

Table 1 also reports the second order autocorrelations of the fund returns. The stylized stale pricing model assumes that all the assets are priced within two months. This implies that the measured returns have an MA(1) time-series structure, and the second order autocorrelations should be zero. The largest second order autocorrelation in the panel is 14.9%, with an approximate standard error of $1/\sqrt{T} = 1/\sqrt{159} = 7.9\%$. For the portfolio of all funds, where the number of observations is the greatest, the second order autocorrelation is -7.1%, with an approximate standard error of $1/\sqrt{543} = 4.3\%$. Thus, none of the second order autocorrelations is significantly different from zero, consistent with the assumptions of the model.

3.2 Bond Market Factor Data

We use daily and weekly data to construct monthly empirical factors. Most of the data are from the Federal Reserve (FRED) and the Center for Research in Security Prices (CRSP) databases. The daily interest rates are from the H.15 release. The factors reflect the term structure of interest rates, credit and liquidity spreads, exchange rates, a mortgage spread and two equity market factors. The Appendix provides the details.

Table 2 presents summary statistics for the monthly series starting in January of

1962 or later, depending on data availability, and ending in December 2007. Missing values are excluded and the units are percent per year (except for the US dollar index and Equity values, represented as the price/dividend ratio). Panel A presents the levels of the variables and panel B presents the monthly first differences. The time-averaged values used as controls for interim trading effects look similar to the levels in Panel A and are not shown.

The average term structure slope was positive, at just over 80 basis points during the sample period. The average credit spread was about one percent, but varied between 32 basis points to about 2.8%. The average mortgage spread over Treasuries was just over 2% for the period starting in 1971, and varied between -0.4% to 5.6%. The liquidity spread averaged 0.4%, with a range between -0.15% and 2.2% over the 1971-2007 period.

In their levels the variables shown in Table 2 are highly persistent time series, as indicated by the first order autocorrelation coefficients. Five of the nine autocorrelations exceed 95%. Moving to first differences, the series look more like innovations.¹¹ We use the first differences of these variables to represent the factor changes in our analysis.

3.3 Style Index Returns

We form style-related benchmark returns for the mutual funds using two alternative methods. The first method is to simply assign a benchmark based on a fund's most recently-declared style. This has the advantage that the benchmark is determined *ex ante* and nothing has to be estimated. It has the disadvantage of relying on the fund's self-declared style.

¹¹ Given the relatively high persistence and the fact that some of the factors have been studied before exposes us to the risk of spurious regression compounded with data mining, as studied by Ferson, Sarkissian and Simin (2003). However, Ferson, Sarkissian and Simin (2008) find that biases from these effects are largely confined to the coefficients on the persistent regressors, while the coefficients on variables with low persistence are well behaved. Thus, the slopes on our persistent control variables and thus the regression intercepts may be biased, but the market timing coefficients should be well behaved.

If a fund strategically misrepresents its style or is more accurately represented as a hybrid style, then the benchmark will be inaccurate.

We select seven benchmarks based on funds' declared styles. Global funds are paired with the Lehman Global Bond Index. Short-term bond funds are paired with a portfolio of US Treasury bond returns with less than or equal to 48 months to maturity. This best matches the reported maturities of their holdings (see the Appendix). Mortgage funds are paired with the Lehman US Mortgage Backed Securities Index. Corporate bond funds are paired with the Lehman US AAA Credit Index, while High-yield funds are paired with the Merrill Lynch High-Yield US Master Index.¹² For two of the styles we use combinations of Lehman bond indexes, weighted in proportion to their contributions to the Lehman US Aggregate bond index. Because Government style funds hold significant amounts of mortgage-backed securities in the latter part of the sample period, we pair the Government bond funds with a combination of the Lehman mortgage backed index and a long-term Treasury bond index.¹³ Finally, we pair the catch-all Other bond funds and the Index funds with a combination of the Treasury bond index, the mortgage backed index and the corporate bond index.¹⁴

¹² We splice the Blume, Keim and Patel (1991) low grade bond index returns prior to 1991, with the Merrill Lynch High Yield US Master Index returns after that date.

¹³ We splice the Ibbotson Associates 20 year government bond return series for 1962-1971, with the CRSP greater than 120 month government bond return after 1971.

¹⁴ The aggregate weights are from Lehman (2006), in percent:

Year	Government	Credit	Mortgage
1976	49	42	5
1986	56	19	23
1996	52	17	30
2001	34	27	35.

We use the most recent ex ante weight to form the benchmark in a given year. Prior to 1977 we pair the Government funds with the long-term Treasury return index and we pair the Other and Index funds with the Corporate bond index.

Our second, alternative method follows Sharpe (1992). Historical returns are used to estimate a fund-specific tracking portfolio of passive asset class returns. This has the advantages of not relying on a fund's self-declared style and of allowing a fund to be represented as a hybrid style. It has the disadvantage that the portfolio weights must be estimated, and the estimates will be imprecise for funds with a limited sample of returns. If the portfolio weights for a particular period are estimated using any future returns data, there may be a look-ahead bias in the analysis for the future period. The details of this approach are discussed in the Appendix.

Panel B of Table 1 presents the Sharpe style-index weights for the style-based portfolios. The weights present sensible patterns, suggesting that both the style classification of the funds and Sharpe's procedure are reasonably valid. The Global funds load most heavily on global bonds. Short term funds have most of their weight in bonds with less than 48 months to maturity. Mortgage funds have their greatest weights on mortgage backed securities. Corporate funds have more than 70% of their weight in high or low grade corporate bonds. High yield funds have 77% of their weight in low grade corporate bonds. Government funds do load highly on mortgage-backed securities (21%), consistent with the observations of Comer (2006) and Moneta (2008).

4. Empirical Results

We first examine the empirical relations between the factors and passive investment strategies proxied by the style benchmarks. We evaluate the effects of the controls for nonlinearities on these portfolios and on broad portfolios of the mutual funds. We then apply the models to individual funds.

4.1 Factor Model Regressions

We begin the empirical analysis with regressions of the style benchmark returns on

changes and squared changes in the factors, looking for convexity or concavity. Nonlinearities suggest what would happen given a naive application of the timing regression (1) for funds, if funds simply held the benchmark portfolios. If the benchmark returns are nonlinearly related to the factors, it suggests that controls for nonlinearities could be important.

Table 3 summarizes the t-ratios for the regression coefficients on the squared factors. Only t-ratios that exceed 1.6 in absolute value are shown; otherwise a zero is recorded. Panel A of Table 3 shows that out of 72 cases (8 styles times 9 factors) there are 25 heteroskedasticity-consistent t-ratios with absolute values larger than 1.6. Nine of the absolute t-ratios are above 2.0. Thus, there is significant evidence of nonlinearity in the benchmark returns. Most of the large coefficients are positive, indicating convexity. Using the Sharpe style benchmarks (not shown in the table) the evidence for convexity is even stronger. This implies that we would measure positive timing ability, based on regression (1), if funds simply held the benchmarks. Thus, controlling for nonlinearity of the benchmark returns is likely to be important for measuring the timing ability of bond funds.

Comparing the funds with the benchmarks, we see the effects of active management. The coefficients for the mutual funds are summarized in Panel B of Table 3. Here we find 11 absolute t-ratios larger than two and 19 in excess of 1.6. This is more than expected by chance; thus, the mutual fund returns are significantly nonlinearity related to the factors.¹⁵ The coefficients on the squared factors are negative in about half of the cases. Thus, the fund returns appear more concave in relation to the factors than do the benchmark returns. This might suggest poor market timing ability on the part of the mutual funds, but we would not expect to find much evidence of market timing for an entire style portfolio of mutual funds. More likely, nonlinearity

¹⁵ Using a simple binomial model assuming independence, the t-ratio associated with finding 11 "rejections," when the probability of observing a rejection is 5%, is $(11/72 - .05)/(.05(.95)/72)^{0.5} = 4.00$.

that differs from the benchmark reflects derivatives, interim trading, public information or stale pricing effects that are not found in the benchmarks. Note that marginally significant t-ratios are found for the index funds on three of the nine factors, as shown in the first row of Panel B. This further suggests that the nonlinearity is unrelated to timing, as index funds are unlikely to be actively market timing.

We also examine regressions like Table 3 where the fund style returns net of the benchmark returns are the dependent variables. The evidence of concavity is much stronger in these regressions, as would be expected. We find 27 or 28 absolute t-ratios larger than 1.6 and all but one or two are negative, depending on the type of style benchmark. Thus, simply measuring fund returns net of a benchmark will not control for the nonlinearities. If we naively ran the regression (1) using fund returns net of benchmark returns on the left hand side, we would find strong evidence of negative timing ability.

Finally, Table 3 reports the adjusted R-squares of the regressions when all nine factors and their squares are included. We would expect the R-squares to be higher for the benchmarks than for the funds if active management in the form of security selection creates nonsystematic noise in the funds. We would expect higher R-squares for the funds if managers are primarily timing systematic factors. A large difference in the R-squares could also indicate bad benchmarks. The average R-squared across the funds is 51.6% and the average across the benchmarks is 53.8%.

4.2 Evaluating the Controls

The next step in the analysis is to evaluate the impact of the controls for non-timing-related nonlinearity in the general model represented by Equations (2) and (9). To control for benchmark nonlinearity the function $b_B(f_t)$ is used. We consider three specifications for $b_B(f)$: Quadratic, exponential and piecewise linear. As described earlier, a quadratic function can be

motivated by coskewness. An exponential function can be motivated by a continuous-time model, however, since $e^f \approx 1+f$ when f is numerically small, the linear function well approximates the exponential for small factor changes. We find no empirically measurable impact of an exponential function, compared with a linear function.

The piecewise linear specification is $b_B(f) = bf + c f^* I(f>0)$, where $I(f>0)$ is an indicator function for a positive change in the factor. A piecewise linear function can be motivated as approximating an option payoff. We use zero as the breakpoint in the piecewise linear function for simplicity and to avoid estimating a breakpoint parameter. This will be useful when we apply the model at the level of the individual funds, where short time series often limit the degrees of freedom.

We revisit the factor model regressions of Table 3 using the piecewise linear function in place of the quadratic function to capture nonlinearity. The results for the benchmark returns are similar. The coefficient, c , is positive, indicating convexity in the benchmarks, and the t-ratio is large in significant fractions of the cases. The coefficients for the fund portfolios are again a mix of positives and negatives, with large t-ratios in a significant fraction of the cases. The funds are typically more concave in the factor changes than are the benchmarks.

Table 4 summarizes the impact of the controls for non-timing-related nonlinearity on the funds grouped into the broad style categories. We do not expect to find significant timing ability at the level of the broad style portfolios, so a well-specified model should produce insignificant timing coefficients. The models are estimated one factor at a time and the table summarizes the averages of the timing coefficients and the average t-ratios taken across the nine market factors.

In Panel A the benchmark is modeled as a piecewise linear function of the factor changes. The second column shows the results with no other controls. Here we find negative

average timing coefficients for seven of eight styles, with half of the average t-ratios less than -2.0. The index funds' average t-ratio is -2.2. These results confirm the impressions from Table 3 that naive market timing regressions would find "negative" timing ability, and show that controlling for nonlinearity in the benchmarks alone is not adequate to control for non-timing related nonlinearity in funds' returns.

The third column of Panel A introduces the controls for public information effects in the models with piecewise nonlinear benchmarks. The average timing coefficients are still negative, but none of the average t-ratios is below -2.0. The effect of the public information controls is similar to what Ferson and Schadt (1996) find for equity funds: with the controls the funds' timing performance looks somewhat better and we no longer find significant "negative" timing ability.

The columns labelled Interim Trading and Stale Pricing in Panel A introduce these controls alone, to the model with a piecewise nonlinear benchmark, while the All Controls uses all of the controls simultaneously. Under the stale pricing controls we find six of the eight average timing coefficients are negative and half of the average t-ratios are less than -2.0, which is very similar to the model with the nonlinear benchmark only. Thus, the influence of stale pricing on the average results is small. With the interim trading controls only two of the average t-ratios is negative and all of the t-ratios are small. The interim trading controls have the greatest impact on the average results. Controlling for interim trading increases the timing coefficients, making the funds' adjusted returns appear less concave (more convex) relative to the benchmark. This suggests that on average funds' interim trading or derivatives positions have the effect of selling convexity. That is, instead of mimicking the purchase of call or put options, which induce convexity, funds' interim trading has the opposite effect of inducing concavity. Purchasing callable bonds, for example, induces concavity because the fund is effectively short the call option. When we control for interim trading effects we remove this concavity from the measured returns.

In the right hand column of Panel A all of the controls are used together. We find that only two of the eight average coefficients are less than zero, and all of the average coefficients and t-ratios are small, which is consistent with a well-specified model. We repeat the analysis of Panel A using a quadratic function to model benchmark nonlinearity in place of the piecewise linear function. All of the impressions are very similar to those in Panel A, so we do not tabulate the results.

In Panel B of Table 4 we repeat the analysis without controls for nonlinear benchmarks. With no controls the results are even more perverse than in Panel A. Three of the eight average t-ratios for the timing coefficients are below -3.0, and the average t-ratio for the index funds is -3.02. Thus, controlling for nonlinearity in the benchmarks is important.

Table 4 evaluates the average effects of the controls, but we conduct further experiments that focus on the effects of the controls in the tails of the cross-sectional fund distributions. To do this we use the style and characteristics-based fund portfolios. In one experiment we examine the fractions of the cases where the t-ratios for the timing coefficients are in the tails; that is, above +2.0 or below -2.0, sorting the cases by fund style or by factor. There are 180 possible cases for each style (9 factors times 20 characteristics-sorted portfolios) and 160 possible cases for each factor. When there are no controls for nonlinearity we find negative timing coefficients on the fund-characteristic portfolios, as we would expect from the evidence in tables 3 and 4. Introducing the quadratic or piecewise controls for benchmark nonlinearity has a substantial impact on the extreme values of the timing coefficients. In most of the cases the controls for benchmark nonlinearity reduces the incidence of large t-ratios, relative to the models with no controls. The controls for interim trading, stale pricing and public information have a smaller impact on the tails. Thus, combined with the evidence in Table 4, it appears that the strong effect of the interim trading controls is concentrated in the center of the distribution.

We run an alternative version of this experiment, where the model with all the

controls is compared with models where one control at a time is removed. Here, we find that the controls for interim trading, stale pricing and public information have marginally significant effects, with interim trading being the largest.

We draw several conclusions from this analysis. First, it is important to control for nonlinearity in funds' benchmarks with respect to the factors. Second, on average it appears that funds' interim trading or derivatives activities have the effect of "selling convexity," and this explains the lion's share of the otherwise puzzling concavity in funds' returns as functions of the common factors. Finally, a model that combines the various controls with nonlinear benchmarks produces an overall distribution of the timing coefficients that appears neutral to perhaps slightly positive at the level of fund portfolios.

4.3 Fund level Analysis

We expect to find little timing ability when funds are grouped into broad style portfolios, but there could be individual funds with timing ability. We estimate the market timing coefficients by combining equations (2) and (9) for each fund with at least 36 monthly returns. The results using the piecewise linear $b_B(f)$ function and all of the controls are summarized in Table 5 (the results are similar using the quadratic function as noted below).

There are at least 1100 eligible funds for each factor, and we summarize the distributions of the timing coefficients across the funds. The first column lists selected fractiles of a null distribution of estimated timing coefficients. For each factor we set the timing coefficient in regression (9) equal to zero and simulate the return of each fund as the fitted values of the regression with this modification, plus the randomly resampled residuals. The number of simulated returns is equal to the number of funds. Estimating the model on this simulated data for each fund, we sort the timing coefficients and find the critical values at each fractile. The fractions in the remaining columns are the fractions of the estimated timing coefficients in the

original fund data that exceed these critical values. (For left tail areas we show the fractions that lie below the critical values.)

To evaluate these figures, consider a binomial random variable that equals 1.0 with probability p , when a timing coefficient is larger than the critical value for the fractile p . If the correlation of the trials is ρ the variance of the fraction of funds above the critical value is $[p(1-p)\{1/n - (1-1/n)\rho\}]$. The correlation ρ depends on the correlation of the funds' returns. We approximate ρ by estimating the pairwise correlations of all the funds' returns using all pairs with at least 36 months in common. The summary statistics in Table 1 suggest that if two funds' return series are separated by more than a month in calendar time, their average correlation is statistically zero.¹⁶ We therefore scale each contemporaneous correlation by the fraction of the sample where the two fund return series overlap. We make the conservative assumption in this calculation, that the correlations at one lag are equal to the contemporaneous correlations and we set the correlations beyond lag one to zero. The resulting estimate of ρ is 0.083. This implies that the standard deviations of the fractions in Table 5 are approximately 0.14, 0.085, 0.06 and 0.045 respectively, for the 0.50, 0.10, 0.05 and 0.025 fractiles.

Overall, the timing coefficients are mildly skewed toward positive values, relative to the null distributions, excepting the coefficients on the slope and curvature factors, which are mildly negatively skewed. For most of the factors, however, the distributions of the coefficients are not significantly different from the null distributions. For the US dollar factor, we do find significant positive timing, with more than 82% of the funds' timing coefficients above the median from the null distribution, but the 5% and 2.5% tails conform closely to the null distribution.

(Using the quadratic $b_B(f)$ there are significant positive timing coefficients in the tail as well.)

¹⁶ Recall that the autocovariance of a portfolio return is approximately the average of the lagged cross covariances of the securities in the portfolio. Since the second order autocorrelations in Table 1 are statistically zero, this indicated insignificant average lagged cross correlations beyond the first lag.

There is marginally significant evidence that some funds can time the credit, liquidity and equity value factors. For the curvature factor, we find more negative coefficients, with only 28% of the funds' coefficients above the median from the null distribution. (Using the quadratic $b_B(f)$ the negative coefficients are significant below the median.)

Panel B reports the estimated correlations of the timing coefficients with the ten fund characteristics described earlier. With about 1200 observations, the standard error of these correlations is about 0.03. There are 38 out of 171 correlations larger than 0.06. Assuming a 5% significance for two standard errors from the mean, the binomial t-statistic accounting for correlation across trials equal to 0.08, is 2.7. Thus, there are significant correlations. The strongest correlations with the timing coefficients are found for the short rate, slope and US dollar factors. For these, timing is negatively related to the expense ratio, the lagged return and the global style dummy, but the other correlations are mixed.

4.4 Timing-adjusted Performance

The idea in most measures of investment performance is to compare the average return of a managed portfolio over some evaluation period to the return of a benchmark portfolio. The benchmark portfolio ideally represents a feasible investment alternative to the managed portfolio. If the objective is to evaluate the investment ability of the portfolio manager or management company, the benchmark should be equivalent in all of the return-relevant aspects to the managed portfolio being evaluated, except that it should not reflect the investment ability of the firm or manager. Aragon and Ferson (2007) call such a portfolio an "*Otherwise Equivalent*" (OE) portfolio. In order to operationalize the OE portfolio it is necessary to have a model to determine what aspects of a portfolio or its return should lead to higher or lower expected returns. Perhaps the simplest example is the CAPM, where the relevant characteristic is the market beta, leading to Jensen's (1968) alpha as the measure of performance.

The intercept in the Treynor-Mazuy regression (1) has been naively interpreted as a "timing adjusted" selectivity measure in several studies. This is incorrect, except in unlikely special cases of stylized "perfect" market timing ability, as discussed by Aragon and Ferson (2007). The reason the intercept does not properly measure performance is that f_t^2 is not a portfolio's excess return. However, the model can be modified to capture the difference between the return of the fund and that of an OE portfolio. Our approach to performance measurement in the presence of market timing follows Aragon and Ferson (2007).

Let r_{h2} be the excess return of the maximum-squared-correlation portfolio for the squared factor changes, f_t^2 . This portfolio is estimated by the regression:

$$f_t^2 = a + \mathbf{H}'\mathbf{r}_t + \mathbf{u}_t \quad (10)$$

where the weights that define the mimicking portfolio r_{h2} are proportional to the regression coefficients, \mathbf{H} . The base assets in \mathbf{r}_t are the seven assets we use to form the Sharpe style benchmarks, excluding the short term Treasury rate, and the returns are in excess of the Treasury rate. The expected value of the excess return, $E(r_{h2})$ is the risk premium associated with the squared factor, which we call the convexity premium.¹⁷ Our goal is to form an OE portfolio for each fund that has the same loadings on its style benchmark and r_{h2} as does the fund. This makes the simplifying assumption that style benchmark exposure and timing are the return-relevant characteristics. The fund's performance is its average return net of what the unmanaged strategy

¹⁷ An alternative approach is to use cross-sectional regressions of returns on betas to estimate mimicking portfolios and factor risk premiums. While we have a large cross section of mutual funds, using the funds with this approach would contaminate the premium estimates with the abnormal returns due to manager ability, if any. We have a small cross section of passive benchmark assets. We therefore use time-series as opposed to cross-sectional regressions to estimate the mimicking portfolios. (See Balduzzi and Robotti, 2007 for comparisons of the two methods.)

would cost to produce these return characteristics. Our measure of alpha is the excess return of the fund net of the excess return of its OE portfolio. The OE portfolio is formed using the following regression:

$$r_{pt} = a_p + b_p r_{Bt} + c_p r_{Bt-1} + d_p r_{h2t} + e_p r_{h2t-1} + v_t \quad (11)$$

The loading on the benchmark, r_B , is estimated following Scholes and Williams (1977) as $\beta_p = b_p + c_p$ to account for stale pricing in the fund returns. Similarly, the loading on the hedge portfolio is $\Omega_p = d_p + e_p$. The OE portfolio return for fund p is $\beta_p r_B + \Omega_p r_{h2}$.

Table 6 presents the analysis of timing adjusted performance. The second and third columns of Panel A summarize the mean excess returns over a short term Treasury and the mean returns over the style benchmarks at selected fractiles of their distributions across the funds. The average excess returns are percent per month. The remaining columns of Panel A of Table 6 report the fractions of funds with alphas larger than (for the right tail and median) or smaller than (for the left tail) the critical values for the indicated fractiles from the null distribution in which the true alphas are zero. Panel B summarizes the average risk premiums for the squared factors (denoted convexity premiums), which are the average excess returns of mimicking portfolios for the squared factors. It also summarizes the distributions of loadings on style benchmarks and the hedge portfolios for the squared factors.

The median fund excess return is 0.46% per month, about 20 basis points below the mean in Table 1. The median return net of benchmark is -0.07%, consistent with previous studies that find bond funds return less than benchmarks on average. The distribution is skewed to the left, with 5% of the funds below -0.28% and 5% above 0.10%.

The third column of Table 6 shows the values of the estimated alphas that define various fractiles of the distribution across funds under the null hypothesis that the true alphas are

zero. These critical values suggest that the estimates of alpha have smaller variation than the average returns net of the style benchmarks. Thus, the alphas should provide more precision in measuring performance than the returns net of benchmark. For example, the range between the top and bottom 10% of the alphas is 0.13%. The range is 0.23% for the returns net of benchmark.

Many funds appear to have significantly negative timing-adjusted alphas.

Depending on the factor, 78-86% of the funds have alphas below the median value of zero under the null. Between 10-18% of the funds have alphas below -0.15% per month, which is at the left 2.5% tail of the null distribution. The alphas in the right tails, by contrast, are not significantly different from the null distributions. The table provides strong evidence of negative timing-adjusted performance on an after-cost basis.

Panel B of Table 6 digs more deeply into the structure of the timing adjusted alpha analysis. We first summarize the funds' loadings on the style benchmarks. Funds' loadings vary widely in the cross section, with the 10% tails spanning loadings between 0.42 and 1.38. This shows that the returns net of benchmark are crude performance measures. They assume that all of the betas equal 1.0.

The average convexity premiums vary from -2.93% per month for equity volatility to 3.5% for equity values, but funds' loadings on these factors are small and the range is narrow, with 80% of the funds between -0.12 and +0.09. The rest of the convexity premiums are an order of magnitude smaller than the equity-related convexity premiums, but the range of funds' loadings is somewhat larger.

If market timing or convexity is valuable, we expect negative return premiums for portfolios that are positively correlated with squared factor changes. This implies that the convexity premiums, given by the mean of r_{h2} , multiplied by the sign of the correlation between the maximum-squared-correlation portfolio and the factor changes should be negative. This correlation is shown in the last line of Table 6. The product is negative for each of the nine

factors, excepting the interest rate curvature factor.

The largest effect of the timing adjustments on funds' required returns is the short rate convexity factor exposure, which contributes $(0.415)(0.134)=0.06\%$ per month for a fund in the upper ten percentile. (A positive loading on the r_{h2} corresponds to concavity with respect to interest rate changes, for which characteristic a slightly higher return is required.) For the median fund the affect is slightly positive. For a given fund return, these positive timing adjustments imply smaller timing-adjusted alphas.

We estimate the correlations of the alphas with the ten fund characteristics described earlier. Statistically significant correlations are found, with 68 out of 171 correlations in excess of 0.06. The strongest correlations are again found when the factors are the short rate and term slope, although significant correlations are found for other factors. We find a strong negative relation of alpha to the fund expense ratio and a positive relation to turnover for all factors. These correlations are consistent with what other studies have found for equity funds. There is also positive correlation with the Corporate and Global style dummies, and a weak negative relation with the fund's reported yield.

4.5 Before-Cost Performance

Since the OE portfolio pays no trading costs while the bond funds do, the alphas reflect a mixed message. This is consistent with the approach in much of the performance measurement literature. If investors could replicate the OE portfolios at negligible cost, then the alphas proxy for the value added that funds generate for investors. In this section we repeat the analysis with the funds' returns measured on a before-cost basis. If a fund returns more than the OE portfolio on a before cost basis, we have evidence of investment ability. To obtain the before-cost returns we add back the average expense ratio plus a measure of trading costs. The trading costs for each fund are a round-trip trading cost estimate based on the fund's style multiplied by

the average reported turnover of the fund.¹⁸

Table 7 presents the results. The median fund return is about 0.11% higher than in Table 6, reflecting a total cost of about 1.3% per year. The median return net of the style benchmark is 0.03% per month, which suggests some investment ability for the median fund. The distributions of the before-cost alphas are markedly different from those in Table 6. About 75% of the funds generate before-cost alphas above the median of the distribution generated under the null hypothesis that the before cost alphas are all zero. Between 10-15% of the funds have alphas above 0.149% per month, which is at the upper 2.5% tail of the null distribution. The alphas in the left tails, by contrast, are not significantly different from the null distributions. This makes sense in that a fund with significant "negative ability" to time market factors, even on a before cost basis, presents a potentially valuable signal to a competitor who can take the opposite position.

Comparing tables 6 and 7, the story is similar to what the literature finds for equity funds. After costs a significant number of funds have poor performance, and not many can generate significant positive performance. Before the costs are subtracted, just the opposite is true.¹⁹ A significant number of funds have positive investment ability, and the performance is

¹⁸ The round trip transaction cost figures are as follows. For Global bond funds we use 31 basis points, based on figures in Bias and Declerk (2006). This is an average of twice the half-spreads from their Table 5 plus the information content from their Table 10, weighted in proportion to the numbers of eurobonds and Sterling bonds in their sample. For corporate bonds we use 48 basis points and for high yield bonds we use 75 basis points. These figures are averages from Edwards, Harris and Piwovar (2007), Bessembinder, Maxwell and Venkataraman (2006) and Hotchkiss et al. (2006) for intermediate trade sizes. For Government funds we use 12.5 basis points, following Ferson, Henry and Kisgen (2006). For Mortgage funds and Short-term funds we use 20 basis points. For Index funds and Other bond funds, we use the average of these figures, or 34 basis points. We checked these figures with a trader at Smith-Breden, John Sprow, who suggested the figures for Mortgage and Short-term bond funds and confirmed that the other numbers seemed reasonable for trade sizes typical of mutual funds under average market conditions.

¹⁹ Gutierrez, Maxwell and Xu (2008) recently find negative after-cost and positive before-cost performance in a sample of Corporate bond funds, and some evidence of persistence in performance.

consistent with the null of no ability in the left tails. Overall, the evidence is consistent with the view that bond fund managers have investment ability but investment fees and trading costs absorb the superior returns, leaving no value for fund investors.

5. Concluding Remarks

Models of market timing using returns measure convexity in the relation between the fund's return and the common factors. However, convexity or concavity is likely to arise for reasons unrelated to timing ability. We adapt classical market timing models to bond funds by controlling for other sources of nonlinearity, such as the use of dynamic trading strategies or derivatives, portfolio strategies that respond to publicly available information, nonlinearity in the benchmark assets and systematically stale prices. These issues should also arise in equity funds, so future research should examine similar controls in the context of equity funds.

We find that controlling for non-timing-related nonlinearity matters, and naive applications of market timing models without these controls would be misleading. Bond funds' returns are typically more concave, in relation to a broad set of bond market factors, than are unmanaged benchmarks. Thus, without controls for non-timing-related nonlinearity, funds would appear to have poor (i.e., negative) market timing ability. When we introduce the controls the distribution of the timing coefficients appears neutral at the fund style-group level and neutral to slightly positive in the sample of individual mutual funds.

The magnitudes of the timing-related components of funds' average returns are typically small, and funds' timing adjusted alphas are significantly negative overall, on an after-cost basis. When we add expense ratios and estimates of trading costs based on fund turnover back to the funds' returns, the adjusted performance is markedly better. About 75% of the funds earn positive before-cost alphas, adjusted for market timing, and the distribution of fund performance is significantly better than would be expected under the null hypothesis that alpha is zero. Thus,

we find evidence of investment ability in bond funds, but no evidence of value added for investors who can trade unmanaged benchmarks at negligible cost.

Our paper contributes to the emerging literature on bond fund performance by laying out a set of methodological issues and suggesting questions that deserve more research. We find that simple returns net of style benchmarks are not likely to be reliable performance measures because funds' loadings on the benchmarks differ substantially from 1.0. More precision is available with our alpha estimates that adjust for timing-related nonlinearity.

Goetzmann et. al (2000) find that successful market timing at a daily frequency by equity funds may produce returns that do not show up as convexity in monthly returns; so monthly data may have low power to detect market timing ability. Bollen and Busse (2001) find evidence of timing ability for equity funds using daily data. Future research should adapt our approach to study timing using daily data. Non-timing-related nonlinearities are likely to remain important in daily data, while daily bond fund returns data present new challenges. For example, income distributions are sometimes treated as accrued interest in bond funds (Morey and O'Neal, 2005) which complicates the interpretation of daily returns. However, the potentially improved power motivates more work along these lines.

Appendix

A.1 Market Timing Models

Assume that the fund manager combines a benchmark portfolio with return R_B and a short-term Treasury security or "cash" with known return R_F . The portfolio weight on R_B is $x(s)$, where s is the private timing signal. The managed portfolio return is $R_p = x(s)R_B + [1-x(s)]R_F$. The signal is observed and the weight is set at time $t-1$, the returns are realized at time t , and we suppress the time subscripts when not needed for clarity. In the simplest example the factor changes and the benchmark's excess returns are related by a linear regression (we allow for nonlinearities below):

$$\mathbf{r}_{Bt} = \mu_B + \mathbf{b}_B \mathbf{f}_t + \mathbf{u}_{Bt} \quad (\text{A.1})$$

where $\mathbf{r}_B = \mathbf{R}_B - \mathbf{R}_F$ is the excess return, $\mu_B = \mathbf{E}(\mathbf{r}_B)$, the factor changes are normalized to have mean zero and \mathbf{u}_{Bt} is independent of \mathbf{f}_t . Assume that the signal $\mathbf{s} = \mathbf{f} + \mathbf{v}$, where \mathbf{v} is an independent, mean zero noise term with variance, σ_v^2 . The manager is assumed to maximize the expected value of an increasing, concave expected utility function, $\mathbf{E}\{U(\mathbf{r}_p)|\mathbf{s}\}$. Finally, assume that the random variables $(\mathbf{r}, \mathbf{f}, \mathbf{s})$ are jointly normal and let $\sigma_f^2 = \text{Var}(\mathbf{f})$. With these assumptions the optimal portfolio weight of the market timer is:²⁰

$$\mathbf{x}(\mathbf{s}) = \lambda \mathbf{E}(\mathbf{r}_B|\mathbf{s})/\sigma_B^2, \quad (\text{A.2})$$

where $\lambda > 0$ is the Rubinstein (1973) measure of risk tolerance, which is assumed to be a fixed parameter, and $\sigma_B^2 = \text{Var}(\mathbf{r}_B|\mathbf{s})$, which is a fixed parameter under normality.

The implied regression for the managed portfolio's excess return follows from the optimal timing weight $\mathbf{x}(\mathbf{s})$ and the regression (A.1). We have $\mathbf{r}_p = \mathbf{x}(\mathbf{s}) \mathbf{r}_B$, then substituting from (A.1) and (A.2) and using $\mathbf{E}(\mathbf{r}_B|\mathbf{s}) = \mu_B + \mathbf{b}_B [\sigma_f^2/(\sigma_f^2 + \sigma_v^2)] (\mathbf{f} + \mathbf{v})$, we obtain equation (1), where $\mathbf{a}_p = \lambda \mu_B^2/\sigma_B^2$, $\mathbf{b}_p = (\lambda \mu_B \mathbf{b}_B/\sigma_B^2) [1 + \sigma_f^2/(\sigma_f^2 + \sigma_v^2)]$ and $\Lambda_p = (\lambda/\sigma_B^2) \mathbf{b}_B^2 [\sigma_f^2/(\sigma_f^2 + \sigma_v^2)]$. The error term \mathbf{u}_{pt} in the regression is a linear function of \mathbf{u}_B , \mathbf{v} , $\mathbf{v}\mathbf{u}_B$, $\mathbf{f}\mathbf{u}_B$ and $\mathbf{v}\mathbf{f}$. The assumptions of the model imply that the regression error is well specified, with $\mathbf{E}(\mathbf{u}_p | \mathbf{f}) = \mathbf{0} = \mathbf{E}(\mathbf{u}_p) = \mathbf{E}(\mathbf{u}_p \mathbf{f}^2)$.

The model shows that timing ability implies convexity between the fund's return

²⁰ The first order condition for the maximization implies:

$\mathbf{E}\{U'(\cdot)|\mathbf{r}_B|\mathbf{s}\} = \mathbf{0} = \mathbf{E}\{U'(\cdot)|\mathbf{s}\} \mathbf{E}\{\mathbf{r}_B|\mathbf{s}\} + \text{Cov}(U'(\cdot), \mathbf{r}_B|\mathbf{s})$, where $U'(\cdot)$ is the derivative of the utility function. Using Stein's (1973) lemma, write the conditional covariance as: $\text{Cov}(U'(\cdot), \mathbf{r}_B|\mathbf{s}) = \mathbf{E}\{U''(\cdot)|\mathbf{s}\} \mathbf{x}(\mathbf{s}) \text{Var}(\mathbf{r}_B|\mathbf{s})$. Solving for $\mathbf{x}(\mathbf{s})$ gives the result, with $\lambda = -\mathbf{E}\{U'(\cdot)|\mathbf{s}\}/\mathbf{E}\{U''(\cdot)|\mathbf{s}\} > 0$.

and the systematic factor changes, independent of the direction of the relation between the factor changes and the benchmark return. That is, since $\lambda > 0$ the coefficient $\Lambda_p \geq 0$, independent of the sign of b_B . If the manager does not receive an informative signal then $\Lambda_p = 0$ because $E(r_B|s)$ and $x(s)$ are constants.

A.2 Nonlinearity

The manager's market-timing signal is now assumed to be $s = b_B(f) + v$, where v is normal independent noise with variance, σ_v^2 . This captures the idea that the manager focuses on the return implications of information about the factor changes.

The optimal weight function in (A.2) obtains with:

$$E(r_B|s) = \mu_B [\sigma_v^2 / (\sigma_f^{*2} + \sigma_v^2)] + [\sigma_f^{*2} / (\sigma_f^{*2} + \sigma_v^2)] \lambda a_B + b_B(f) + v, \text{ where } \sigma_f^{*2} = \text{Var}(b_B(f)).$$

Substituting as before we derive the nonlinear regression for the portfolio return:

$$r_{pt} = a_p + b_p [b_B(f_t)] + \Lambda_p [b_B(f_t)^2] + u_t \quad (\text{A.3})$$

with:
$$a_p = \lambda a_B (\mu_B \sigma_v^2 + a_B \sigma_f^{*2}) / (\sigma_B^2 (\sigma_f^{*2} + \sigma_v^2)),$$

$$b_p = \lambda (\mu_B \sigma_v^2 + 2a_B \sigma_f^{*2}) / (\sigma_B^2 (\sigma_f^{*2} + \sigma_v^2)),$$

and
$$\Lambda_p = (\lambda / \sigma_B^2) / (\sigma_f^{*2} + \sigma_v^2).$$

The reduced form Equation (3) of the text ignores some of the restrictions in (A.3); for example, if $b_B(f)$ is quadratic there are restrictions involving f^3 and f^4 . In our data we find that these higher order terms are empirically negligible. For this reason we replace $b_B(f_t)^2$ with f_t^2 in Equation (3).

A.3 Screening the Fund Sample

There are a total of 40,390 fund-year records in our initial sample. In order to

address back-fill bias we remove the first year of returns for new funds, and any returns prior to the year of fund organization, a total of 2,625 records. Data may be reported prior to the year of fund organization, for example, if a fund is incubated before it is made publicly available (see Elton, Gruber and Blake (2001) and Evans, 2006). Extremely small funds are more likely to be subject to back-fill bias. We delete cases where the reported total net assets of the fund is less than \$5 million. This removes 5,698 records. We delete all cases where the reported equity holdings at the end of the previous year exceeds 10%. This removes 1,017 records. We identify cases where funds report multiple share classes. Multiple classes are identified when two ICDI codes for the same year have a common fund name and a different share class code. We retain the share class with the largest Total Net Assets and delete the other share classes. This removes another 10,723 records. After these screens we are left with 20,236 fund-years. The number of funds with some monthly return data in a given year is four at the beginning of 1962, rises to 14 at the beginning of 1973, to 564 by 1993 and to 1,054 at the beginning of 2007.

A.4 Funds Grouped by Characteristics

The fund characteristics include age, total net assets, percentage cash holdings, percentage of holdings in options, reported income yield, turnover, load charges, expense ratios, the average maturity of the funds' holdings, and the lagged return for the previous year. Each year we sort the funds of a given style with nonmissing characteristic data from high to low on the basis of the previous year's value of a characteristic and break them into thirds. We form equally weighted portfolio returns from the funds in the high group and the low group for each month of the next year.

We examine various summary statistics of the fund characteristics grouped by style. The reported turnover is used when we compute our proxy for before-cost returns, and is interesting as an indicator of active management. We find that the low-turnover Index funds

have the lowest turnover (increasing from 8 to 59% per year over the 1992 to 2006 period) and the high-turnover Corporate funds have the highest turnover (increasing from 117 to 202% between 1992 and 2006). Turnover increases over the sample period for all styles except the High-yield funds. If turnover is largely driven by the need to replace maturing bonds, for example, one might expect to find that the Short term funds have the highest turnover. This is not the case. For example, the highest-turnover third of each fund style reports more turnover than the lowest third of the Short-term funds. There is more cross-sectional variation of turnover within a style group than across the fund styles. Thus, the turnover figures suggest active management of the bond funds.

A.5 Bond Market Factor Data

Three factors represent the term structure of Treasury yields: A short-term interest rate, a measure of the term slope and a measure of the curvature of the yield curve. The short-term interest rate is the three-month Treasury rate. The slope of the term structure is the ten-year yield less the one-year yield. The curvature measure is: $y_3 - (y_7 + 2y_1)/3$, where y_j is the j -year fixed-maturity yield.

Since our funds hold corporate bonds subject to default risk and mortgage backed securities subject to prepayment risks, we construct associated factors. Our credit spread series is the yield of Baa corporate bonds minus Aaa bonds, from the FRED. These series are measured as the weekly averages of daily yields. We use the averages of the weeks in the month for our time-averaged version of the spread. For the discrete changes in the spread we use the first differences of the last weekly values for the adjacent months. The first difference series may not be as clean as with daily data, but we are limited by the data available to us. Our mortgage spread is the difference between the average contract rate on new conventional mortgages, also available weekly from the FRED, and the yield on a three-year, fixed maturity Treasury bond. Here we use daily

data on the Treasury bond and weekly data on the mortgage yield to construct the time averages and discrete changes.

For market timing we are interested in market-wide fluctuations in liquidity. Our measure follows Gatev and Strahan (2006), who advocate a spread of commercial paper over Treasury yields as a measure of short term liquidity in the corporate credit markets. (See also, Bernanke (1983) who interprets the spread as a monetary policy factor.) We use the yield difference between three-month nonfinancial corporate commercial paper rates and the three month Treasury yield. The commercial paper rates are measured weekly, as the averages over business days.

Some of the funds in our sample are global bond funds, so we include a factor for currency risks. Our measure is the value of the US dollar, relative to a trade-weighted average of major trading partners, from the FRED. This index is measured weekly, as the averages of daily figures, and we treat it the same way we treat the other weekly data. Corporate bond funds, and high-yield funds in particular, may be exposed to equity-related factors. We therefore include two equity market factors in our analysis. We measure equity volatility with the VIX-OEX index implied volatility. This series is available starting in January of 1986. We also include an equity market valuation factor, measured as the price/dividend ratio for the CRSP value-weighted index. The dividends are the sum of the dividends over the past twelve months, and the value is the cum-dividend value of the index. The level of this ratio is a state variable for valuation levels in the equity market, and its monthly first difference is used as a factor.

A.6 Sharpe Style Indexes

Following Sharpe (1992) we combine the asset class returns, R_i , using a set of portfolio weights, $\{w_i\}$, to minimize the "tracking error" between the return of the fund group, R_p , and the portfolio, $\sum_i w_i R_i$. The portfolio weights are required to sum to 1.0 and must be non-

negative, which rules out short positions:

$$\text{Min}_{\{w_i\}} \text{Var}[R_p - \sum_i w_i R_i], \quad (\text{A.4})$$

subject to: $\sum_i w_i = 1, w_i \geq 0$ for all i ,

where $\text{Var}[\cdot]$ denotes the variance. We solve the problem numerically. The asset class returns include US Treasury bonds of three maturity ranges from CRSP (less than 12 months, less than 48 months and greater than 120 months), the Lehman Global bond index, the Lehman US Mortgage Backed Securities index, the Merrill Lynch High Yield US Master index and the Lehman US Credit Aaa bond index.

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Table 1

Mutual Fund Monthly Returns: Summary Statistics. The sample periods for the fund returns are January of the year indicated under Begin through March of 2007. Nobs is the number of nonmissing time series observations, Begno is the number of funds at the start of the sample period and Endno is the number in March of 2007. The returns are percent per month. Mean is the sample mean, std is the sample standard deviation, ρ_1 is the first order sample autocorrelation and ρ_2 is the second order autocorrelation. Panel B presents the portfolio weights of Sharpe style benchmarks associated with each group of funds. The benchmarks are formed from the returns to US Treasury bonds with less than or equal to 12 (le12) 48 (le48) months to maturity, greater than 120 months to maturity (gt120), a high-grade corporate bond index (cb), a low-grade corporate bond index (junk), a global bond index (global) and a mortgage-backed securities index (mort). The weights are estimated using all available months from 1976 through 2007.

Panel A: Equally-weighted Portfolios of Mutual Funds

Style	Begin	nobs	Begno	Endno	Mean	Min	Max	Std	ρ_1	ρ_2
All	1962	543	4	1054	0.617	-5.397	9.770	1.511	0.25	-0.01
Index	1991	195	1	18	0.546	-3.609	3.907	1.122	0.14	-0.07
Global	1994	159	47	54	0.436	-3.483	4.557	1.455	0.16	-0.08
Short Term	1993	171	126	217	0.369	-0.856	2.267	0.455	0.30	0.15
Government	1986	255	1	127	0.547	-3.817	4.318	1.248	0.14	-0.12
Mortgage	1991	195	10	61	0.491	-2.411	3.188	0.854	0.20	0.01
Corporate	1962	543	4	308	0.627	-7.339	10.97	1.691	0.18	-0.03
High Yield	1991	195	34	135	0.737	-6.900	7.535	1.835	0.25	0.08
Other	1964	543	1	134	0.661	-5.103	9.609	1.640	0.22	0.001

Panel B: Sharpe Style Benchmarks

Funds	Weights assigned to asset classes:							Autocorrelations:	
	le12	le48	gt120	cb	junk	global	mort	ρ_1	ρ_2
All	0.00	0.12	0.03	0.35	0.25	0.05	0.19	0.19	-0.03
Index	0.07	0.20	0.21	0.26	0.03	0.02	0.20	0.14	-0.04
Global	0.00	0.00	0.00	0.22	0.17	0.61	0.00	0.20	-0.02
Short Term	0.54	0.19	0.00	0.14	0.02	0.03	0.08	0.21	-0.01
Government	0.06	0.13	0.21	0.36	0.00	0.03	0.21	0.13	-0.03
Mortgage	0.09	0.00	0.02	0.21	0.00	0.00	0.67	0.13	-0.05
Corporate	0.00	0.15	0.07	0.55	0.17	0.02	0.04	0.17	-0.03
High Yield	0.00	0.10	0.00	0.00	0.77	0.00	0.13	0.21	-0.003
Other	0.00	0.00	0.00	0.29	0.39	0.06	0.27	0.20	-0.02

Table 2

Summary Statistics for the bond market factor data. The sample periods begin as indicated under Starts (yyymm), and all series end in December of 2007. Nobs is the number of time series observations, excluding missing values. The units are percent per year, except the US dollar (an index number) and Equity values (a price to dividend ratio). Mean is the sample mean, std is the sample standard deviation and ρ_1 is the first order sample autocorrelation of the series.

Panel A: Levels of the Factors

Factor	Starts	Nobs	mean	min	max	std	ρ_1
short rate	196201	540	5.847	0.904	16.38	2.842	0.981
term slope	196201	539	0.836	-3.160	3.310	1.115	0.955
curvature	196907	450	0.168	-1.097	0.773	0.286	0.834
credit spread	196201	551	0.989	0.320	2.820	0.418	0.961
mortgage spread	197104	393	2.184	-0.410	5.580	0.821	0.839
liquidity spread	198211	290	0.402	-0.151	2.179	0.345	0.658
US dollar	197101	443	110.3	84.48	167.7	14.77	0.986
Equity Values	196201	540	36.54	16.27	71.18	13.24	0.992
Equity Volatility	198601	252	19.77	10.63	61.41	6.940	0.798

Panel B: First differences of the Factors

short rate	196202	539	0.0041	-4.158	2.611	0.539	0.132
term slope	196202	537	-0.0016	-1.460	2.800	0.334	0.130
curvature	196908	449	-0.0004	-0.807	0.770	0.164	-0.292
credit spread	196202	550	0.0007	-0.550	0.680	0.116	0.063
mortgage spread	197105	392	0.0049	2.110	3.240	0.461	-0.097
liquidity spread	198212	289	0.0004	-1.845	1.718	0.286	-0.399
US dollar	197102	442	-0.0652	-8.132	8.694	2.318	0.159
Equity Values	196202	539	0.0233	-6.630	6.508	1.615	-0.035
Equity Volatility	198602	251	-0.0319	-15.28	39.03	4.388	-0.193

Table 3

Regressions of bond funds and benchmark index returns on changes in factors and their squares. The sample starts in February of 1962 or later, depending on the factor and fund style, and ends in March of 2007. The t-ratios for the regression coefficients on the squared factor changes are shown when they exceed 1.6 in absolute value; otherwise a zero is shown. These are based on regressions with a single factor and its square. R^2 is the adjusted coefficient of determination in a regression featuring the changes in all nine factors and their squared changes.

Style group	short	slope	curve	credit	mort.	liquid	US dollar	equity values	equity volatility	$R^2(\%)$
Panel A: Style Benchmarks										
Index	0.000	1.93	0.000	1.88	0.000	0.000	0.000	0.000	2.20	65.1
Global	0.000	1.64	0.000	0.000	0.000	1.99	0.000	0.000	3.29	57.1
Short Term	1.69	2.69	0.000	2.51	0.000	1.66	0.000	0.000	2.94	60.0
Government	0.000	1.96	0.000	1.88	0.000	0.000	0.000	0.000	2.22	65.4
Mortgage	0.000	2.08	0.000	1.88	0.000	1.74	0.000	0.00	2.63	51.5
Corporate	0.000	1.78	0.000	1.86	0.000	1.83	0.000	0.000	0.000	58.4
High Yield	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-1.92	0.000	30.7
Other	0.000	1.68	0.000	1.71	0.000	2.51	0.000	0.000	0.000	41.9
Panel B: Funds by Style										
Index	-1.81	0.000	0.000	-1.90	0.000	0.000	2.40	0.000	0.000	65.8
Global	-2.08	0.000	0.000	0.000	0.000	-1.75	2.48	0.000	0.000	47.4
Short Term	0.000	0.000	0.000	-1.97	0.000	0.000	0.000	0.000	0.000	3.5
Government	0.000	0.000	0.000	-2.23	0.000	0.000	2.45	0.000	2.38	63.1
Mortgage	0.000	0.000	0.000	-2.03	0.000	0.000	1.63	0.000	0.000	54.5
Corporate	0.000	0.000	0.000	0.000	0.000	1.85	0.000	0.000	0.000	55.3
High Yield	0.000	0.000	0.000	3.31	0.000	0.000	2.44	-2.78	-3.58	42.2
Other	0.000	0.000	0.000	1.62	0.000	2.49	0.000	0.000	0.000	40.9

Table 4

The effects of controls for non-timing-related nonlinearity on funds groups' timing coefficient estimates. The table records the average of the timing coefficients and the average t-ratios across nine market factors. The models are estimated one factor at a time on monthly data for 1962-2007, with 543 or fewer observations depending on the fund group and factor combination. Only benchmark is the baseline model with a possibly nonlinear benchmark but no other controls. Public Information introduces only the controls for public information effects, and similarly for the columns labelled Interim Trading and Stale Pricing, while All Controls uses all of the controls simultaneously for the given factor.

Fund Style	Only Benchmark	Public Information	Interim Trading	Stale Pricing	All Controls
Panel A: Piecewise Linear Benchmarks					
Index	-9.98e-005 -2.20	-8.76e-005 -1.54	6.15e-005 0.0298	-3.10e-005 -2.12	5.97e-005 -0.104
Global	-0.000204 -2.19	-0.000161 -1.70	-2.73e-005 -0.203	-6.61e-005 -2.17	6.40e-005 0.174
Short Term	-0.000148 -2.70	-6.15e-005 -1.55	1.29e-005 -0.549	-8.01e-005 -2.54	2.18e-005 -0.252
Government	8.86e-006 -1.16	2.16e-005 -1.12	0.000154 0.244	4.17e-005 -1.26	0.000128 0.148
Mortgage	-0.000177 -2.33	-9.47e-005 -1.47	2.33e-005 0.0757	-7.65e-005 -2.28	6.21e-005 0.243
Corporate	-5.37e-005 -0.0129	-0.000124 -0.163	2.76e-005 0.290	9.65e-005 0.535	0.000169 0.903
High Yield	-0.000145 -1.57	-0.000108 -1.01	0.000144 0.207	-3.13e-005 -1.42	0.000157 0.592
Other	8.63e-005 0.506	3.37e-005 0.304	0.000204 1.04	0.000171 1.07	0.000260 1.74
Panel B: Linear Benchmarks					
Index	-0.000312 -3.02	-0.000328 -3.02	-0.000102 -0.893	-0.000199 -3.11	-3.25e-005 -0.638
Global	-0.000262 -2.68	-0.000264 -2.82	-6.43e-005 -0.611	-0.000170 -2.79	-1.58e-005 -0.390
Short Term	-0.000257 -3.26	-0.000254 -3.08	-7.93e-005 -1.36	-0.000188 -3.16	-5.30e-005 -1.31
Government	-0.000190 -1.78	-0.000212 -2.17	-3.37e-005 -0.482	-0.000120 -1.89	4.30e-006 -0.413
Mortgage	-0.000293 -3.13	-0.000307 -3.08	-9.10e-005 -1.08	-0.000194 -3.20	-3.63e-005 -0.806
Corporate	-0.000129 -0.214	-0.000219 -0.467	-1.44e-005 0.205	6.34e-005 0.604	0.000149 1.06
High Yield	-0.000308 -2.31	-0.000425 -2.47	4.43e-005 -0.153	-0.000193 -2.34	4.08e-005 0.0572
Other	2.41e-005 0.200	-0.000118 -0.304	0.000178 0.769	0.000105 0.701	0.000192 1.33

Table 5

Timing coefficients of individual bond funds. Panel A summarizes the fractions of funds with timing coefficients larger than (for the right tail and median) or smaller than (for the left tail) the critical values for the indicated fractiles from the null distribution in which the true timing coefficients are zero. Panel B presents the correlations of the timing coefficients with various fund characteristics. The monthly samples start in February of 1962 or later, depending on the factor and fund, and end by March of 2007.

null fractile	short	slope	curve	credit	mortgage	liquidity	dollar	equity value	equity volatility
Panel A: The distributions of the timing coefficients									
0.975	0.0182	0.0086	0.0390	0.0286	0.0597	0.0510	0.0273	0.0296	0.0235
0.950	0.0316	0.0133	0.0640	0.0715	0.0989	0.0926	0.0640	0.0428	0.0839
0.900	0.0893	0.0250	0.126	0.153	0.151	0.168	0.235	0.0763	0.252
0.500	0.547	0.395	0.278	0.742	0.684	0.732	0.824	0.765	0.706
0.100	0.211	0.178	0.174	0.0469	0.0526	0.0322	0.0406	0.0530	0.0729
0.0500	0.153	0.100	0.0476	0.0167	0.0303	0.0157	0.0257	0.0241	0.0455
0.0250	0.0996	0.0469	0.0187	0.0127	0.0214	0.0126	0.0179	0.0078	0.0298
# cases	1265	1278	1282	1259	1122	1274	1282	1284	1275
Panel B: Correlations of timing coefficients with fund characteristics									
expenses	-0.1520	-0.2100	-0.0102	0.0407	-0.1230	-0.0130	-0.0491	0.0570	0.0202
turnover	0.0388	0.0587	-0.0105	-0.0087	-0.0298	-0.0242	-0.0213	-0.0124	-0.0010
flow	0.0052	0.0138	0.0005	-0.0220	0.0916	-0.0978	-0.0478	0.0158	-0.0176
cash	-0.0587	-0.0135	0.0339	-0.0372	-0.0365	-0.0301	-0.1460	0.0542	-0.0332
net assets	-0.0268	0.0462	-0.0142	-0.0036	-0.0017	0.0164	0.0041	-0.0068	0.0179
options	-0.0497	-0.0121	-0.0096	-0.0042	-0.0157	0.0274	0.0484	-0.0044	0.0358
yield	-0.1430	-0.0547	-0.0590	0.0438	-0.1660	0.0918	0.1540	-0.0240	-0.0276
age	0.0329	-0.1860	-0.0613	0.0669	-0.0724	-0.0146	0.0053	-0.0056	-0.1050
lag return	-0.1570	-0.3020	-0.1270	0.1030	0.1340	-0.0536	-0.0925	0.8830	0.2430
maturity	0.0301	-0.0146	-0.0794	0.0579	0.0440	-0.0425	0.0758	0.0018	0.0597
load	-0.1670	-0.0982	-0.0200	0.0359	-0.0577	0.0529	0.0115	0.0249	0.0296
Index	-0.0021	0.0688	-0.0091	-0.0126	0.0147	-0.0443	0.0247	-0.0108	0.0053
Global	-0.0957	-0.1510	-0.0409	-0.0316	0.1650	-0.0358	-0.158	0.0077	0.0602
Short Term	0.0647	0.0829	-0.0093	-0.0150	-0.0344	0.0470	-0.0938	-0.0184	-0.0956
Government	0.0286	0.1120	-0.0274	-0.0163	0.0558	-0.0343	-0.0280	-0.0118	0.0040
Mortgage	0.0493	0.0877	-0.0020	-0.0131	-0.0133	0.0182	-0.0054	-0.0063	-0.0451
Corporate	-0.0221	0.1690	-0.0008	-0.0045	0.0216	-0.0919	-0.0171	-0.0285	0.0070
High Yield	-0.2010	0.0004	0.0298	0.0003	-0.0285	0.0586	0.1800	0.0230	0.0801
Other	-0.0852	0.0007	-0.0366	-0.0076	-0.0213	0.1960	0.1320	-0.0032	0.2220

Table 6

Timing adjusted performance of individual bond funds. The first three columns of Panel A summarize the mean excess return over a short term treasury, the mean return over a style benchmark, and the values of the estimated alphas under the null hypothesis that the true alphas are zero, taken at various fractiles of the distribution across funds. The average excess returns are percent per month. The remaining columns report the fractions of funds with alphas larger than (for the right tail and median) or smaller than (for the left tail) the critical values for the indicated fractiles from the null distribution in which the true alphas are zero. Panel B summarizes the average risk premiums for the squared factors (denoted convexity premium), which are the average excess returns of mimicking portfolios for the squared factors. It also summarizes the distributions of loadings on the style benchmarks and on the hedge portfolios for the squared factors. The monthly samples start in February of 1962 or later, depending on the factor and fund, and end by March of 2007.

fractile	mean return	mean net of bench	critical alpha	short	slope	curve	credit	mort.	liq.	dollar	equity value	equity vol.
Panel A: The distribution of Timing Adjusted Alphas												
0.975	0.818	0.171	0.150	0.023	0.031	0.024	0.018	0.020	0.010	0.021	0.023	0.017
0.950	0.715	0.104	0.099	0.053	0.051	0.044	0.029	0.036	0.014	0.048	0.046	0.046
0.900	0.632	0.036	0.061	0.079	0.071	0.074	0.051	0.066	0.030	0.069	0.071	0.068
0.500	0.463	-0.067	-0.000	0.217	0.216	0.205	0.192	0.198	0.143	0.214	0.217	0.220
0.100	0.285	-0.199	-0.064	0.419	0.428	0.384	0.448	0.447	0.532	0.396	0.408	0.403
0.050	0.193	-0.282	-0.108	0.268	0.242	0.205	0.248	0.260	0.341	0.232	0.186	0.222
0.025	0.100	-0.386	-0.156	0.138	0.130	0.108	0.181	0.153	0.188	0.139	0.109	0.134
# cases				1329	1368	1375	1251	1179	697	1357	1376	1376
Panel B: Convexity premiums and loadings												
Fund Loadings on Benchmarks:												
Upper 10%				1.38	1.40	1.35	1.42	1.38	1.40	1.38	1.38	1.33
Median				0.91	0.91	0.91	0.89	0.89	0.91	0.91	0.92	0.90
Lower 10%				0.42	0.43	0.45	0.48	0.43	0.46	0.45	0.42	0.43
Average Convexity premiums				0.415	0.231	-0.332	0.107	0.144	-0.029	-0.244	3.59	-2.93
Fund Convexity Loadings:												
Upper 10%				0.134	0.145	0.054	0.130	0.226	0.103	0.064	0.091	0.093
Median				0.005	0.012	0.001	0.003	0.006	-0.001	-0.0001	-0.006	0.0001
Lower 10%				-0.224	-0.128	-0.065	-0.163	-0.209	-0.129	-0.0775	-0.118	0.072
Correlations of Hedge Portfolios: with Squared factor changes				-0.278	-0.383	-0.308	-0.215	-0.456	0.160	0.510	-0.273	0.532

Table 7

Timing adjusted performance of individual bond funds gross of transactions costs. Transactions costs are estimated as the average expense ratio of each fund plus an assumed round trip trading cost associated with the fund style, multiplied by the average reported turnover. These costs are added back to the fund return. The first three columns of Panel A summarize the mean excess return over a short term treasury, the mean return over a style benchmark, and the values of the estimated alphas under the null hypothesis that the true alphas are zero, taken at various fractiles of the distribution across funds. The average excess returns are percent per month. The remaining columns report the fractions of funds with alphas larger than (for the right tail and median) or smaller than (for the left tail) the critical values for the indicated fractiles from the null distribution in which the true alphas are zero. The monthly samples start in February of 1962 or later, depending on the factor and fund, and end by March of 2007.

fractile	mean return	mean net of bench	critical alpha	short	slope	curve	credit	mort.	liq.	dollar	equity value	equity vol.
The distribution of before cost Timing Adjusted Alphas												
0.975	0.952	0.318	0.149	0.158	0.113	0.144	0.101	0.110	0.141	0.161	0.132	0.155
0.950	0.855	0.239	0.104	0.257	0.198	0.239	0.184	0.197	0.228	0.258	0.251	0.256
0.900	0.768	0.176	0.063	0.430	0.390	0.377	0.360	0.335	0.412	0.409	0.407	0.425
0.500	0.572	0.032	-0.000	0.767	0.754	0.763	0.746	0.730	0.761	0.742	0.753	0.768
0.100	0.389	-0.081	-0.067	0.091	0.091	0.088	0.093	0.097	0.090	0.100	0.094	0.093
0.050	0.303	-0.145	-0.114	0.046	0.059	0.056	0.066	0.060	0.052	0.061	0.055	0.058
0.025	0.241	-0.225	-0.169	0.031	0.042	0.028	0.043	0.044	0.033	0.040	0.034	0.037
# cases				1329	1367	1374	1251	1178	1375	1357	1375	1375