Measuring Bond Mutual Fund Performance with Portfolio Characteristics

(Job Market Paper)

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Abstract

Employing a novel data set of portfolio weights from 1997 to 2006, the performance of taxable bond mutual funds is studied. The timing ability of fund managers is examined considering different asset allocation choices such as asset class, credit quality allocation, and portfolio maturity decisions. I show that active managers engage in strategies of rotating their portfolios across fixed-income sectors and bond characteristics. Some bond funds exhibit successful timing ability by adopting these strategies. Comparing fund returns plus expenses and transaction costs with the returns of a portfolio that is invested in the previously disclosed holdings, I document that active managers exhibit some ability to select securities that deliver better returns than the securities in the indices. In particular, on average, active managers generate gross returns of 1% per annum over the benchmark portfolio constructed using past holdings. This is approximately enough to cover expenses and transaction costs. Using portfolio data therefore reveals a more optimistic picture of active bond portfolio management, relative to the findings in the existing literature.

JEL classification: G11, G23

Keywords: Bond mutual funds; Performance evaluation; Portfolio holdings

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1 Introduction

In this paper the performance of bond mutual funds is studied using portfolio holdings information. In particular, asset allocation weights are used. That is the proportion of the managed portfolio invested in different fixed income asset classes such as Treasury, corporate, mortgage, foreign bonds, and cash, and in different portfolio characteristics such as credit quality and maturity. I use what is called a weights-based approach (using information about the composition of the managed portfolio) to measure performance instead of using a returns-based approach (using only mutual fund returns information) employed in the existing bond fund literature.[1] The main contribution of this work is therefore to use portfolio holdings information to study bond mutual funds' performance. Three main research questions are addressed in this paper. First, do active fixed-income managers engage in strategies of rotating their portfolios across fixed-income styles[2]? If the answer to the first question is positive, the second question is do active managers of fixed-income mutual funds exhibit skills by changing their asset allocation? Finally, by examining both net and gross returns, can we determine whether there is evidence of selectivity ability and value added for investors?

One challenge in assessing the performance of a managed portfolio is deciding how to deal with the dynamics created by the portfolio weights' changes and the potential time-variation in returns and portfolio characteristics. This is likely to be particularly relevant for bond portfolios for which characteristics such as duration and credit quality are expected to change over time. Moreover, 76% of the bond funds included in this sample change their style (as defined by Morningstar) at least once over the life of the fund. Almost 40% of the bond funds change the investment category (as defined by Morningstar) at least once over the life of the fund. Bond funds also engage in considerable trading activity and in moving the portfolio across different asset classes and characteristics. To date, studies of bond fund performance have used a returns-based approach.[3] Although this has some benefits, due to its minimal information requirement, it can provide an incorrect inference in this context. Early studies such as Jensen (1972) and Grinblatt and Titman (1989) show that the traditional Jensen measure is biased for a market-timing investment strategy and it can assign negative performance to a market timer.[4] Ferson and Schadt (1996) show that inferences about managerial

[1] For equity mutual funds, the performance measures based on portfolio holdings appear to detect superior ability of the managers (see, inter alia, Grinblatt and Titman 1993, Daniel et al. 1997, Wermers 2000, Chen et al. 2000, and Jiang et al. 2007). Using this approach, researchers find more optimistic results about the performance of active portfolio managers.

[2] The term "style" is generally used to indicate a portfolio of assets characterized by a unique risk-return pattern.

[3] Comer (2006) uses annual holdings information to evaluate government bond fund sector timing skill.

[4] Roll (1978) demonstrates that, if the benchmark is inefficient, it is always possible to find another inefficient benchmark that switches the performance ranking based on Jensen alpha. Dybvig and Ross

performance can change significantly after adjusting for time-variation in risk loadings. However, when information about portfolio weights is available, the literature indicates that it is possible to infer abnormal performance in a more robust and powerful manner.

The portfolio holding methodology provides a performance measure as shown by Grinblatt and Titman (1993) which can detect superior performance even in the presence of a market-timing investment strategy (Elton and Gruber, 1991). This methodology can also allow for the separation of timing and selectivity ability as shown by Daniel et al. (1997).[5] Holdings data allow the researcher to construct hypothetical returns that do not include fees and trading costs. These gross returns are more appropriately used to answer questions related to investment ability, since they can be compared to a benchmark that also ignores expenses and transaction costs. The net returns (after fees and costs) are more appropriately used to investigate whether a fund adds value for investors. In this way it is possible "to distinguish this situation from one where the manager has investment ability, but either extracts the rents from this ability in the form of fees and expenses, or dissipates it through trading costs" (Ferson and Aragon, 2008).[6] Another advantage of using a weights-based approach is that there is less reliance on a specific asset pricing model. This is particularly important in the context of bond mutual funds. Indeed, for the fixed-income market it is less clear which equilibrium pricing model should be used for performance evaluation. Finally, other advantages of using portfolio holdings include the possibility of decomposing the sources of performance and having more power to detect fund managers' ability as shown by Kothari and Warner (2001) for equity funds and Comer (2006) for government bond funds.[7]

In one of the first and most cited studies on bond mutual fund performance, Blake et al. (1993) conclude that "the lack of available bond index funds for individual investors, coupled with the high transaction costs that accompany small purchases, might account for the past appeal of actively managed bond funds, despite substantial under-

(1985) show that a manager with superior information can appear to observers to have inferior performance using the security market line except when the superior information is only security specific.

[5] One way to separate timing from selectivity using a returns-based approach is to estimate a regression proposed by Treynor and Mazuy (1966), which includes the squared excess return of the benchmark portfolio as an additional regressor. However, estimation of this type of regression for bond funds' returns appears challenging due to several non-timing related sources of nonlinearities such as option-like features in the underlying assets or dynamic trading strategies (see Jagannathan and Korajczyk, 1986 and Chen at al. 2006).

[6] As noted by Wermers (2006) an examination of fund managers' abilities before expenses and costs is important: "For example, a manager may hold talents in picking securities, but is handicapped by a fund that is too small, making the scale of the fund too expensive to support (through the expense ratio). Identifying such a manager may allow a restructuring of the fund (i.e. through a merger or by creating a new separate account) that overcomes such a handicap while retaining the performance-generating aspects of the fund".

[7] The hypothetical gross returns obtained using portfolio holdings are also more suitable for testing market efficiency than net returns because these are influenced by both the efficiency of the market and the competitiveness of the money management industry (see Schultz 2007).

performance." However, more than a decade later, the opportunities for retail investors have improved substantially. There are more than 30 bond index funds to choose from, which were mainly started in the 1990s. Since 2002, investors have had the opportunity to also invest in several bond Exchange-Traded Funds (ETF). Furthermore, the transaction costs are much lower now and investors can choose from low-cost strategies such as buying newly issued government bonds directly from the Treasury.[8] Nevertheless, the most costly active bond mutual funds experienced intense growth during the 1990's. For example, at the end of 1988 there were 942 bond funds managing $255.69 billion, whereas at the end of 2006 there were almost 2000 bond funds managing almost $1.5 trillion (see Figure 1). It looks like, to paraphrase Gruber (1996), we have another "puzzle" in the growth of active bond funds. This puzzle remains unsolved since more recent studies on bond mutual fund performance such as Ferson et al. (2006) and Chen et al. (2006) did not find evidence of superior performance looking, respectively, at selectivity and timing ability. This debate is important to justify the high trading costs and expenses that active mutual funds charge. For example, the difference between the expense ratio of the average active bond mutual fund and of the largest bond index fund (Vanguard Total Bond Index fund) is roughly 60 basis points which amounts to more than $8 billion per year considering that active bond funds manage approximately $1.4 trillion in assets.

The holdings-based measure that is used in this study is very similar to the Grinblatt and Titman (1993) measure and it is called Characteristic Timing (CT) measure following Daniel et al. (1997). This study differs however because asset class weights are used rather than information about the securities that compose the portfolio. This choice is justified by data availability[9] and by the fact that the fixed-income market is a natural setting to use aggregate weights.[10] The CT measure is the covariance of the portfolio weights with the subsequent returns of indices which match the asset classes. This can also be interpreted as the average dollar return of a zero-cost portfolio: a portfolio invested in the most recent allocations and short in the previously disclosed portfolio allocations updated using a buy-and-hold strategy. A positive figure is evidence of abnormal performance, relative to buy-and-hold. This measure can be calculated using returns data for all trading days (or monthly data) or only announcement days. These are days which contain the most concentrated information about the economy and hence about fund managers' ability to interpret or anticipate public information.[11] Indeed, price

[8] See for instance Jonathan Clemens, "Yield Chase: Boost Income by Slashing Investment Costs", Wall Street Journal, February 14, 2007.

[9] In contrast to equities, it is not feasible to find returns data for all the bonds in the portfolio. Indeed, the universe of fixed-income securities is broader than that of equity securities.

[10] Unlike equities which are difficult to group into meaningful categories, fixed-income securities have closely specified characteristics (that also have a risk interpretation) and cash flows that make them easy to classify. Fixed-income securities also have, in general, little idiosyncratic risk. Bond portfolio's returns are indeed well explained by aggregate benchmark portfolios' returns.

[11] This approach is in the spirit of Baker et al. (2004) who studied whether managers of equity mutual funds have stock-picking skills by comparing their holdings and trades prior to earning announcements

movements in the fixed-income market, especially in the Treasury market, are driven by public information[12].

An attribution analysis is also carried out, where the mutual fund returns and costs are decomposed in the CT measure, in an Average Style (AS)[13] similar to that of Daniel et al. (1997), and in a residual component called return GAP following Kacperczyk et al. (2008). In this case however, the return GAP includes a selectivity component since asset class weights and returns are used instead of single securities. In this way it is possible to assess whether fund managers can add value through selectivity in addition to timing. It is important to examine both timing and selectivity ability because bond funds include ample variety in investment strategies and objectives. Finally, a third measure is the CT estimated using conditional information similar to the conditional weights-based measure suggested by Ferson and Khang (2002). Using conditional information overcomes potential biases that occur if managers use public information to estimate expected returns.

The asset allocation decisions considered in this study involve the allocation across different asset classes such as Treasury, corporate, mortgage, foreign bonds, and cash and changes in portfolio maturity and credit quality. These portfolio weights, obtained by Morningstar for both existing and disappearing funds, have not been used to the full extent in the literature. For the attribution analysis I will use the asset class allocation with adjustments for different credit quality and maturity exposure of each fund vis-à-vis the benchmark constructed using past weights and Merrill Lynch bond indices information. For the CT analysis the three asset allocation decisions will be considered separately. There is some evidence that relative performance between asset classes can be predictable and that a strategy of rotating (timing) across styles can generate significant returns. This has been documented for equity by Asness et al. (2000) and Ahmed et al. (2002), among others, and for the fixed-income market by Amenc et al. (2003). There is also ample evidence of stock market and bond return predictability.[14] However, as noted for equities by Jiang et al. (2007) "there is scant evidence that investors actually take advantage of such predictability in their portfolio decisions. [...] Fund managers are sophisticated and informed investors. If they cannot exploit market return predictability, it is unlikely that anyone else could."

First, evidence that bond mutual funds engage in active strategies is presented. Active

with the returns realized at those events.

[12] Evidence shows that macroeconomic surprises have a significant impact on asset returns and volatility. See, among others, Fleming and Remolona, (1997) and (1999) and Balduzzi et al. (2001). Andersen et al. (2007) showed that the response to real-time US macroeconomic news is larger in the bond markets than in the stock market.

[13] The AS captures the before cost returns earned by a fund due to that fund's tendency to hold fixed-income securities with certain characteristics.

[14] For evidence of bond return predictability see, for instance, Fama and Bliss (1987), Fama and French (1989), and Cochrane and Piazzesi (2005).

bond fund managers trade frequently and significantly more often than managers of bond index funds. The average turnover rate for a sample of almost one thousand active bond funds is 150% (higher for example than equity funds) for the period 1997-2006. Portfolio weight variations are too large to be explained by passive changes in the characteristics of the portfolio and may instead suggest some timing activity. These time-varying asset class weights can also cause a drift in a fund's style. Second, concerning performance, the results show a more optimistic picture, relative to existing results based on a returns-based approach. There is some evidence of timing ability: although the average mutual fund exhibits neutral timing ability (the measure is close to zero), some subgroups of funds exhibit significant positive timing ability. In particular, multi-sector bond funds exhibit timing ability when moving the portfolio across different credit quality ratings and maturity. High yield funds are also successful in changing the credit quality allocation. This timing ability seems short-lived and the CT measure is larger if the performance measure is calculated using days with only macroeconomic announcements. A similar inference is provided using a conditional analysis.

Third, more optimistic results than the returns-based approach are also found when looking at selectivity. Whereas the traditional alpha is significantly negative, the return GAP after expenses and transaction costs is close to zero and becomes positive (although not statistically significant) for some subgroups of funds such as high yield, corporate bond general, Treasury and multi-sector funds. Indeed, on average, mutual funds delivered net returns that are approximately the same as the gross returns of their characteristic benchmarks (the benchmarks constructed using portfolio holdings information). This suggests that mutual fund managers hold securities that beat their benchmarks by almost enough to cover their expenses and transaction costs (on average slightly above 1 percent per year). Fourth, the analysis of sources of asset-allocation performance reveals that managers may have talent in moving their portfolios in the foreign sector, in long-term bonds, AAA corporate bonds and in low quality corporate bonds.

The performance measures examined however do not persist in the following one-year period as suggested by a persistence test although there is evidence of persistence considering a shorter window such as one quarter. To explain this finding and to examine whether some fund characteristics are associated with the CT and return GAP, panel data analyses are conducted. They reveal that the return GAP measure is negatively associated with size and past flows. This suggests diseconomies of scale consistent with the Berk and Green (2004) model and a negative impact of past flows as pointed out by Ferson and Warther (1996) and Edelen (1999). These two effects could contribute to the lack of persistence. Other significant associations are between the return GAP and turnover rate, Morningstar ratings, alpha, and portfolio characteristics such as duration and credit quality. The turnover rate is found to be positively associated with the return GAP. This suggests that the trading activity creates some value. Bond fund managers also appear to be able to earn back their fees since the relation between expenses and the return GAP is positive and statistically significant before fees and insignificant after fees. Return GAP is positively associated with Morningstar rating and alpha. This result is consistent with the interpretation of the return GAP as selectivity ability. Funds with a portfolio with high duration and low credit quality exhibit a higher return GAP. Finally, some differences are found for the CT measures. Funds with positive CT measure are associated with lower cash holdings, larger size, and lower Morningstar ratings.

Finally, similar to Kacperczyk et al. (2008), findings in this study show that the return GAP helps to predict future mutual fund performance. Bond funds with favorable past return GAP deliver an annualized 2.3 percent return and 1.9 percent risk-adjusted return more than funds with poor past return GAP. This is greater than what can be obtained selecting funds using past alphas.

2 Related Mutual Fund Literature

Many researchers have studied equity mutual fund performance. Somewhat different findings are, however, documented depending on how the returns are measured. A first group of papers, including inter alia Jensen (1968), Malkiel (1995) and Carhart (1997), examine the net returns of funds (after transaction costs and expenses). These authors find that active managers fail to outperform passive benchmark portfolios and they appear to destroy value, suggesting that investors are better off holding market indices.

The second group of papers examines the individual equity holdings of mutual funds obtaining gross returns of portfolios that contain only stocks without accounting for transaction costs and expenses. Grinblatt and Titman (1993) propose a portfolio measure, based on portfolio weights, that does not require the use of an explicit asset pricing model.[15] Moreover, this portfolio holding methodology can also overcome a timing-related bias of the traditional method. The Grinblatt and Titman measure is based on the assumption that from the perspective of uninformed investors the vector of expected asset returns is constant over time. Therefore, their portfolio holdings can not be correlated with future asset returns. However, a manager with private or superior information can change his portfolio weights over time toward assets with higher expected returns and away from assets with lower expected returns. Hence, the covariance between the change in a portfolio's weights and subsequent abnormal security return can be used to measure performance. Although the covariance can be negative for a single security, Grinblatt and Titman (1989) prove that the sum of the covariances will be positive for an investor with private information and with nonincreasing Rubinstein absolute risk aversion.

More precisely, the portfolio holdings measures (PHM) are calculated as the covari-

[15] However, an implicit benchmark is still present, which is based on the return earned by the portfolio in the previous period and not on an asset pricing model.

ance between lagged weights and current returns:[16]

$$PHM_t = cov\left(w_{t-1}, R_t\right) = E\left\{w_{t-1}\left[R_t - E\left(R_t\right)\right]\right\} = E\left\{\left[w_t - E\left(w_t\right)\right] R_t\right\} \qquad (1)$$
$$= E\left\{\left[w_t - E\left(w_t\right)\right]\left[R_t - E\left(R_t\right)\right]\right\}$$

The approach requires choices of benchmarks for a managed portfolio and the estimation of $E(w_t)$ and/or $E(R_t)$. Copeland and Mayers (1982) suggest estimating the first expansion of the covariance. The authors use future returns to estimate $E(R_t)$ and to evaluate the performance of Value Line rankings. Grinblatt and Titman (1993) suggest estimating the covariance using $E\{[w_t - E(w_t)] R_t\}$ and using past weights as the best proxy of $E(w_t)$. Using a market or peer-based benchmark portfolio may allow the manager to game the benchmark by overweighting securities with higher expected returns, and underweighting securities with lower expected returns. Using past weights makes it more difficult for a manager to game the measure for any substantial period of time.[17] Future portfolio holdings should not be used because the PHM would be biased for a manager who implements momentum strategies. For example, a manager who overweighs securities with high past returns will exhibit a future weight that is correlated with current returns. The Grinblatt and Titman (GT) measure can be interpreted as the average dollar return of a zero-cost portfolio: a portfolio long in the most recent holdings and short in the past holdings. Ferson and Khang (2002) suggest estimating the last expansion of the covariance: $E\{[w_t - E(w_t)][R_t - E(R_t)]\}$. $E(R_t)$ is estimated using the sample average (in the unconditional measure) and $E(w_t)$ is estimated using past weights updated using a buy-and-hold strategy.

The GT measure includes both timing and selectivity abilities. Daniel et al. (1997) suggest separating the two contributions and decomposing the portfolio performance into two main components: a component called "Characteristic Selectivity" (CS) and another component called "Characteristic Timing" (CT). The latter is a measure of a manager's ability at timing the different investment styles. The difference between CS and CT stems from the use of disaggregate or aggregate information. The CS measure uses information at the security level such as the weight of the fund in a given security and its return. The CT uses information at the aggregate level such as the return of a benchmark. Since information about the single securities is unavailable, I can only estimate a measure similar to the CT measure in this paper.

Other studies using portfolio holdings include Grinblatt et al. (1995), Wermers (1999 and 2000), Chen et al. (2000). The performance measures based on portfolio holdings appear to be more powerful to detect superior ability of the managers. Indeed, these studies find that mutual funds tend to select stocks that outperform a broad market index and outperform passive benchmarks of stocks with similar characteristics.

[16] For a detailed analysis of the different portfolio holding measures see Wermers (2006).

[17] The cost of the GT measure is that it is necessary to observe the lagged weight.

Another group of papers examine whether managers present any timing ability. Timing ability in the context of equity mutual funds is defined as holding common stocks when stocks earn higher return than cash and holding cash equivalents otherwise. Several studies such as Treynor and Mazuy (1966), Henriksson and Merton (1981), Henriksson (1984) and more recently Jiang (2003), do not find evidence of timing ability. Similar results are found in a conditional setting by Ferson and Schadt (1996) and Becker et al. (1999) although conditioning on public information improves the results. Graham and Harvey (1996) also do not find evidence of market timing ability when examining investment newsletters' asset allocation recommendations. However, a more recent paper, Jiang et al. (2007), find that actively managed US domestic equity funds have positive ability on average using a new measure based on mutual fund holdings. This finding is consistent with the idea that equity mutual fund managers are successful at exploiting the predictability in market returns documented in the literature. Positive results are also found when analyses are performed using high frequency (daily) data as shown by Bollen and Busse (2001) for mutual funds and by Chance and Hemler (2001) for a sample of professional market timers.

Very few studies have examined the performance of fixed-income mutual funds. As noted by Ferson et al. (2006), "Recent years have witnessed an explosion of research on the performance of mutual funds, with most of the attention focused on equity-style funds. The amount of work on fixed-income funds is small in relation to their importance in the economy". Blake et al. (1993) and Elton et al. (1995) present the first major analysis of the performance of bond mutual funds. Blake et al. (1993) consider two samples: one of 46 bond funds (for a 10-year period: 1979-1988) and a larger one that includes 223 bond funds (for a 5-year period: 1987-1991). The evidence provided suggests that bond funds underperform post-expenses. Ferson et al. (2006) evaluate government bond mutual fund performance using stochastic discount factors from continuous-time term structure models.[18] These authors confirm that performance after cost is negative but economically small. Chen et al. (2006) study the timing ability of US fixed-income mutual funds. Controlling for potential non-timing related sources of nonlinearity (such as the use of derivatives) they do not find evidence of timing ability. Boney et al. (2009) examine timing ability in a sample of 84 high quality corporate bond funds using variations of Henriksson and Merton (1981) and Sharpe (1992). They find evidence of perverse market timing ability.

I am aware of only one recent study, authored by Comer (2006), that uses holdings information to study bond mutual fund performance. Comer performs a simulation study

[18] Some studies such as Cornell and Green (1991) and Gudikunst and McCarthy (1997) investigated the investment performance of US low-grade bond mutual funds. Other studies evaluated the performance of non-US bond mutual funds. Maag and Zimmermann (2000) studied the performance of German bond mutual funds while Dahlquist et al. (2000) studied the performance of Swedish mutual funds including bond funds. Silva et al. (2003) focused on European bond fund performance.

showing that a standard Treynor and Mazuy (1966) type of regression is relatively weak for identifying timing ability, whereas the use of annual portfolio weights is more powerful for detecting ability despite the limited frequency. Comer (*ibid.*) claims that for a sample of 129 government bond funds, a Sharpe (1992) approach with the use of annual portfolio weights is more powerful to detect ability despite the limited frequency.[19] This study will employ a richer data set from Morningstar Principia. Since data were collected from monthly CD-ROMs since 1997, it is possible to obtain historical information about existing and disappearing mutual funds. More observations can also be obtained since funds report semiannually, quarterly and sometimes even monthly to Morningstar. Moreover, this study will examine many more asset classes and investment objectives, whereas Comer (2006) considered only three asset classes (cash, government/credit and mortgage), and one investment objective (general government). This can improve our understanding of managerial ability across different dimensions and it allows the identification of the main sources of value in the portfolio investment decisions. Finally, this analysis will not be limited to timing ability but will also try to gauge the ability of the managers to select securities that outperform the securities in the index.

3 Research Design

In this section the three performance measures used in this analysis are presented. First, the unconditional CT measure is introduced. This captures the ability of the fund manager to time the various asset allocation decisions and bond characteristics. Second, I present a return decomposition of mutual fund returns and costs that help to better investigate managers' ability and value added to the portfolios. The return GAP measure is obtained from this decomposition. Finally, a conditional approach is used to obtain the Conditional Characteristic Timing (CCT) measure.

3.1 The Unconditional Characteristic Timing (CT) Measure

Following Grinblatt and Titman (1993) and Daniel et al. (1997) past weights are used to estimate $E(w_t)$ in (1), however Ferson and Khang (2002) is followed when considering buy-and-hold weights. Therefore, using past asset allocation weights and bond index returns that match the asset classes the CT measure for fund i is the time-series average

[19] Huij and Derwall (2008) also include some optimistic results about the performance of bond funds. In particular, contrary to previous studies they provide evidence of the performance persistence of a large sample of active bond funds from 1990 to 2003.

of its component at time t, which, in turn is written as:

$$CT_t^i = \sum_{j=1}^{N} \left(w_{j,t-1}^i - \tilde{w}_{j,t-1-k}^i \right) R_{j,t} \tag{2}$$

where $R_{j,t}$ is the total return of the bond index for sector (or credit quality or maturity allocation) j during month t, $w_{j,t-1}^i$ is the weight of fund i in sector j disclosed at the end of month $t-1$, and $\tilde{w}_{j,t-1-k}^i$ is the buy-and-hold weight of fund i in sector j disclosed at the end of the previous period $t-1-k$. More precisely, the buy-and-hold weights for each sector j are calculated updating the disclosed weights $w_{j,t-1-k}^i$ and taking into account the relative performance of the sector from $t-1-k$ to $t-1$:

$$\tilde{w}_{j,t-1-k}^i = \frac{w_{j,t-1-k}^i \prod_{\tau=1}^{k} (1 + R_{j,t-\tau})}{\sum_{j=1}^{N} w_{j,t-1-k}^i \prod_{\tau=1}^{k} (1 + R_{j,t-\tau})} \tag{3}$$

Grinblatt and Titman (1993) suggested using the previous quarter ($k = 3$) and the previous year's ($k = 12$) holdings. They showed, however, that the magnitude of abnormal performance is larger using the previous year's holdings. They also suggest that the choice of the information lag should depend on when the information of the manager is revealed, i.e. whether it is revealed within one quarter or over a longer period. This choice can also be important for one of the assumptions of this measure, that the systematic risk of current portfolio is the same as the systematic risk of past portfolio. Since there are no previous examples of this type of measure for bond funds, I will use both lags.

For this analysis, each asset class weight must be matched with a particular bond index. Lehman Brothers and Merrill Lynch provide an extensive number of broad and specialized bond market indices which cover all the asset classes considered by Morningstar. One "natural" advantage of the weights-based measure is that future returns with different horizons can be used and not just a specific holding-period return. In this way the horizon of the timing ability can be examined. I can also calculate the CT measure using monthly return data and daily return data. When using daily data (for returns and not for weights) I can examine whether better results are obtained by only considering announcement days rather than non-announcement days. These events are likely to be important for assessing the evidence of superior information and abilities of bond fund managers.

The CT measure can be calculated for each fund and different asset class breakdowns provided by Morningstar (see next section). I can then aggregate across time and across mutual funds and test whether the average CT measure is significantly different from zero. I can run the test for all the funds or subgroups of funds to examine whether some specific subgroups earned significantly positive abnormal returns. Moreover, it is possible to identify the main drivers of the abnormal performance without summing across share classes. One approach is to take the weight difference in a particular asset class multiplied by the return of that asset class. However, as Grinblatt and Titman (1993) point out, each of the terms in the sum in (2) need not to be positive for an investor with ability. This is because changes in portfolio weight can be due to diversification reasons. To investigate the source of asset allocation performance, I carry out a test that is similar to Graham and Harvey (1996) focusing on the largest trading decisions which should be more informative to investigate timing ability. These authors studied whether investment newsletters' asset allocation recommendations anticipate the future direction of the market. They examine the average market performance after recommended increases or decreases in weights. This test was also used by Chance and Hemler (2001) to examine the timing ability of professional market timers.

3.2 Mutual Fund Return Decomposition

A portfolio invested in the disclosed portfolio weights can be considered to be a proxy for the gross return of the fund. Using this idea an attribution analysis of bond fund performance can be computed. In particular, the fund return plus expenses and transaction costs can be decomposed into three components: the CT measure, the Average Style (AS) measure, and a residual component that following Kacperczyk at al. (2008) I can call Return Gap (RG). The AS measure was introduced by Daniel et al. (1997) for equity funds. In the fixed-income context, it captures the before cost returns earned by a fund due to that fund's tendency to hold fixed-income securities with certain characteristics. The decomposition is therefore:

$$\begin{aligned} Rp_t^i + EXP_t^i + TC_t^i &= \sum_{j=1}^{N} \left(w_{j,t-1}^i - \tilde{w}_{j,t-1-k}^i \right) R_{j,t} + \sum_{j=1}^{N} \tilde{w}_{j,t-1-k}^i R_{j,t} + RG_t^i \\ &= CT_t^i + AS_t^i + RG_t^i \end{aligned} \tag{4}$$

where Rp_t^i is the return of the mutual fund i for month t, EXP_t^i is an estimate of the monthly expenses (the annual expense ratio divided by 12), and TC_t^i is an estimate of the monthly transaction costs.[20] These costs are approximate, following Chen et al. (2006), using the reported average turnover multiplied by a round-trip transaction cost specific to a given investment objective.[21] Kacperczyk at al. (2008) proposed the return GAP, defined as the difference between the reported fund return and the return of a hypothetical

[20] Other costs, such as load fees and taxes, which are not borne by all the investors will be ignored.

[21] The round-trip transaction cost figures were the same as those used by Chen et al. (2006). More specifically, for high yield funds I used 75 basis points, and for corporate general and high-quality funds I used 48 basis points. For government general and high quality funds I used 12.5 basis points. For mortgage funds I used 20 basis points and for multi-sector funds I used 34 basis points. These figures were divided by 12 to obtain the monthly figures.

portfolio that invests in the previously disclosed holdings after adjusting for expenses. The return GAP is expected to be negatively related to hidden costs and positively related to hidden benefits of a mutual fund. The hidden costs include agency costs and negative investor externalities. The hidden benefits derive from the unobserved interim trades between the last disclosure date and the month t. These benefits also capture high frequency timing not captured by the CT measure. However, in this study the return GAP also includes a selectivity component since I am using asset class weights and returns and not the weights of the securities in the portfolios. Therefore, a fund manager who selects securities which perform better than the securities in the index will obtain a positive return GAP.[22]

3.3 The Conditional Characteristic Timing (CCT) Measure

Another important question is what kind of information is used by the manager when making asset allocation decisions. Ferson and Khang (2002) modify the GT measure by using conditioning information. A set of instruments is used to represent the public information. This enables the authors to disentangle the sources of the manager's performance. In particular, the unconditional covariance in (1) can be decomposed in:

$$cov\left(w_{t-1}, R_t\right) = E\left\{cov\left[w_{t-1}, R_t | Z_{t-1}\right]\right\} + cov\left[w_{t-1}, E\left[R_t | Z_{t-1}\right]\right] \tag{5}$$

The second term on the right-hand side represents performance that is due to the mechanical use of public information. The first term on the right-hand side is the average conditional weight measure. This represents performance in excess of that attributable to using public information to choose the portfolio weights and can be interpreted as manager skill. Following Ferson and Khang (2002), the Conditional Characteristic Timing (CCT) at time t for fund i is:

$$CCT_t^i = \sum_{j=1}^{N} E\left\{\left(w_{j,t-1}^i - \tilde{w}_{j,t-1-k}^i\right)\left(R_{j,t} - E\left[R_{j,t} | Z_{t-1}\right]\right)\right\} \tag{6}$$

where the conditional expected return of index j, $E\left[R_{j,t} | Z_{t-1}\right]$, is estimated running a regression of index returns on conditional information. The CCT measure for fund i is the time-series average of its component at time t. This measure controls for potential

[22] For this analysis only monthly data are used since daily mutual fund returns present problems such as staleness and reporting issues. In particular, according to Morey and O'Neal (2006), the correct treatment of distributions for bond mutual funds requires that income be distinguished from capital gains distributions. This is because capital gains are generally accompanied by a reduction in NAV, whereas income distributions are often treated similarly to accrued interest in bonds. Therefore, the NAV of the fund is quoted without the accrued interest and on the day of the distribution, the NAV will not be reduced.

biases that occur if managers use public information to estimate expected returns.[23] In particular, Ferson and Khang (2002) show that using a conditional weights-based measure approach controls for an interim-trading bias that arises when the manager can trade between observation dates.[24]

4 Data

Four different data sets are used in this study. The first consists of the bond mutual fund data, the second consists of the benchmark returns data, the third consists of predetermined variables that help to predict index returns, and the fourth consists of the macroeconomic announcements.

4.1 Bond Fund Data

Data on bond mutual funds are drawn from the Morningstar Principia monthly CD-ROMs from the beginning of 1997 to the end of 2006 for a total of more than 110 CDs. The CDs provide holdings information. The CDs of Morningstar are provided monthly, but new information about the holdings is generally only updated quarterly or semi-annually. Occasionally, however, monthly updates are available especially in the most recent period. These CDs also include information about fund returns, total net assets, turnover, fees, and several other fund characteristics. Since I collected information that also used past CDs, I retrieved data on both dead and surviving funds. This is an improvement on the few studies that considered a sample of surviving funds from Morningstar. I only considered taxable US bond mutual funds as classified by Morningstar. I therefore excluded municipal bond funds because tax-exemption adds another layer of complication to the analysis. I also excluded international bond funds and money market funds. To ensure an appropriate selection of funds I examined the funds' objectives and portfolio holdings. I excluded funds which invested in any time period more than 50% of their portfolio in equities.[25] Index mutual funds and bond ETFs were also excluded. Similar to Chen et al. (2006), I excluded funds with less than $5 million in net asset value. These are small funds, which are more likely to be subject to the incubation bias

[23] In the context of the fixed-income market, there is evidence that public information such as macroeconomic variables are important to explain expected returns (see, e.g., Elton et al., 1995).

[24] Another way to control for the interim-trading bias is to use additional factors from term structure models as suggested by Ferson et al. (2006).

[25] The mutual funds included in the sample are classified from Morningstar as bond funds (defined as funds with 80% or more of their assets invested in bonds). The average equity allocation is 0.9%, however there are 15 bond funds that invested in at least one instance more than 20% (and less than 50%) of the portfolio in equity.

documented by Evans (2007).[26] I also excluded funds for which I did not have, in any portfolio allocation breakdown, at least 12 weight difference observations (weights of the current portfolio minus weights of some past portfolio) in equation (2) where k is less or equal to 12 months. This filter can potentially cause a survivorship bias. However, this bias should be smaller for bond funds than equity funds.[27] Indeed, Blake et al. (1993) point out that survivorship bias is less important for bond funds because bond fund performance is less variable and, consequently, fewer funds disappear. Moreover, the survivorship bias should not affect the comparison between traditional returns-based performance measures and weights-based measures.

Summary statistics of bond mutual funds for different investment styles for the 1997-2006 period are presented in Table I. A sample of almost 1000 bond mutual funds is considered. The most important category, with respect to the number of funds and total net assets, is general corporate bond funds followed by high quality and general government bond funds. Often, funds report different share classes which have the same holdings composition but different types of fees and loads (see Nanda et al. 2005). On average for every fund, there are almost four share classes. Since the holdings composition is the same for each share class, I aggregate all the observations of the different share classes into one figure. I sum the total net assets (TNA) under management across the different share classes. For other quantitative attributes, I take the weighted averages of the values of the individual share classes with weights proportional to the lagged TNA of the individual share classes. The average expense ratio is 0.8%, slightly lower than that of equity funds. Finally, the last two columns indicate the average yearly net return and the standard deviation.

Two sets of benchmarks are presented in Table I. The first is the return of a portfolio of bond index funds and ETFs which operated during the 1997-2006 period. I present separately the Vanguard Total Bond Index fund. This is the largest bond index fund and the second largest bond mutual fund. The total return of the two main bond indices, the Lehman and Merrill Lynch Aggregate bond index are also shown. At first approximation, as documented by previous studies, investors are better off holding market indices through a low-cost bond index fund.

Table II presents the average turnover rate for different investment objectives and Morningstar categories[28]. Turnover rate is a measure of the fund's trading activity which

[26] The incubation bias stems from the strategy adopted by some fund families to start multiple new funds and to open to the public, after an evaluation period, only the best performing funds.

[27] The sample of all available domestic bond mutual funds in Morningstar between 1997 and 2006 includes 1294 funds, of these there are 435 funds that ceased to exist. If I compare the return of an equally-weighted portfolio of all available funds with the return of only surviving funds the difference is only 0.16% per year. This is smaller that the survivorship bias found for equities. For instance, Grinblatt and Titman (1989) found a survivorship bias of about 0.5% per year.

[28] For taxable bond mutual funds the Morningstar categories are: Long-term government, intermediate-term government, short-term government, long-term bond, intermediate-term bond, short-term bond,

is computed by Morningstar by taking the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing this by the average monthly net assets. For comparison, the table also presents the turnover rate for a sample of actively managed equity mutual funds and for the Vanguard 500 index fund which tracks the S&P500. In general, taxable bond mutual funds trade more frequently than equity funds which have a turnover rate close to 85%. Part of this trading is due to the fact that many bonds change characteristics such as maturity and credit quality. A passive bond index fund, such as the Vanguard Total Bond index, trades more than ten times the Vanguard 500 index fund. Considerable trading seems to occur when a fund is specialized in investing in long-term security and in Treasury and mortgage securities. For example, long-government funds change their portfolio almost every 4 months (three times a year) on average. However, in the definition of turnover, short-term securities with maturity less than one year are excluded. Therefore, the turnover rate for funds specialized in short-term bonds is likely to underestimate the trading activity. These results suggest that active bond fund managers trade frequently. This trading activity will cause higher trading costs relative to the passive funds. It seems important to understand whether managers can create large enough value to compensate for these costs. Moreover, this trading activity can change the exposure of the portfolio and make the task of evaluating manager's performance more challenging.

Morningstar provides different asset allocation breakdowns of the fund's portfolio holdings. The Appendix provides details about these data. In this paper, three portfolio allocations are examined. The first is the portfolio allocation across different asset classes (sectors) of the fixed-income market such as US government bonds, mortgage, credit, foreign bonds, and cash. The second is the portfolio allocation across different credit qualities. The third is the portfolio allocation across different maturity ranges. One weakness of the data is that for many funds there is an irregular distribution of the portfolio weights observations. In some periods, the frequency can be quarterly or even monthly and in other periods there are only annual or semiannual observations. In particular, before 2004, only annual historical portfolio weights are available for the sector allocation. This issue can make statistical inference more challenging. That's also one of the reasons it is important to use a bootstrapping approach to make statistical inference.

4.2 Bond Indices and Instrumental Variables

To calculate the performance measures each asset class must be matched to a bond index (see the Appendix for more details). The two main providers of bond index data are Lehman Brothers (LB) and Merrill Lynch (ML). They provide the main benchmarks for

ultrashort bond, bank loan, world bond, emerging-markets bond, high yield bond and multi-sector Bond.

fixed-income portfolio managers. Both monthly and daily data are used in these analyses. Data on the daily LB and ML bond indices total returns (income, price appreciation and paydown return[29]) were obtained respectively by Lehman Live and Bloomberg. ML indices are used because they provide more daily data available since the beginning of 1997. These index returns are however highly correlated with the corresponding Lehman indices. The portfolios are indeed composed in a similar way. The main difference is that cash accumulated during the month earns a return in the Merrill Lynch indices but not in the Lehman indices. The LB and ML indices are rule-based market-weighted indices whose composition is reset monthly. Rule-based means that for a security to be included in an index, it must satisfy pre-specified criteria. At the end of every month, the composition of the index is reset to include new securities which meet the inclusion rules and exclude securities that were in the index but no longer meet all the criteria (for example bonds that are downgraded or very close to maturity). Finally, I also constructed a value-weighted index of ML sovereign, credit (excluding US) and emerging market indices.[30] Figure 2 shows the annual returns of the main fixed-income asset classes. There is considerable variation in the annual returns with indices switching from the best performing to the worst performing index. This suggests timing opportunities for the talented manager.

The conditional information used includes the following variables: term spread (the difference between the 10-year and 3-month Treasury yield), the 3-month Treasury rate, commercial paper spread (the yield difference between three-month nonfinancial corporate commercial paper rates and the three month Treasury yield), mortgage rate spread (the difference between the average contract rate on new conventional mortgages and the yield on a three-year Treasury bond), default spread (the difference between the yield on BAA corporate bonds and AAA corporate bonds), US dollar exchange rate relative to a trade-weighted average of major trading partners, the VIX index, and the aggregate dividend yield for stocks in the S&P500. Similar lagged information was used by Chen et al. (2006). These variables were obtained from St. Louis Fed FRED database and Datastream. I conducted a preliminary analysis to test whether there is any predictability of the index and mutual fund excess returns. Therefore, a time-series regression of excess returns on the above lagged instrumental variables was performed. This analysis shows that all the lagged information variables with the exception of the mortgage spread help to predict future excess returns of some indices. The regression R^2 adjusted varies between 11 and 18%. Concerning the mutual fund excess return regressions, the T-bill, exchange rate, VIX index and dividend yield are the most important variables to predict future mutual fund excess returns. This provides evidence that manager's returns are

[29] Paydown return is the return related to expected or unexpected payments of principal.

[30] I also tried to use an index of international sovereign debt obtained from MSCI through Datastream. The performance of the investments in the international bond sector looks better using this index probably because it presents an exchange risk component in the total return (the returns are expressed in local currency).

related to public information and provides a motivation for the conditional analysis.

4.3 Macroeconomic Announcements Data

Macroeconomic announcements are publicized events that happen on pre-scheduled dates. For the main analysis, only the announcement dates must be identified. These dates are collected from Bloomberg. A preliminary analysis is also conducted to examine how the different asset class returns respond to macroeconomic announcements. As in previous literature (see for instance Balduzzi et al. 2001) I focus on the surprise component of the announcements. This is measured as the difference between the headline figure and expectations taken from surveys conducted before the releases. For this preliminary analysis I need announcement values and forecasted values that are also obtained from the Bloomberg database. Some missing values concentrated at the beginning of the sample are filled using Factiva. The sample period includes data from the beginning of January 1997 to the end of September 2006. The forecasts are obtained from the median expectation of surveys prepared by Bloomberg News. Following Kuttner (2001), monetary policy surprises are estimated using data from the futures market for Federal funds.

I consider 22 macroeconomic announcements listed in the Appendix. The total number of announcements is more than 2700. The number of trading days which are also announcement days is approximately 62% of the total number of trading days. In an untabulated analysis I estimate a regression of different bond index excess returns during announcement days on each macroeconomic announcement surprise. Consistent with previous literature (e.g. Balduzzi et al., 2001), the majority of the macroeconomic surprises significantly affect bond index excess returns. However, the announcement effect is the weakest for high yield bonds. The fact that the macroeconomic surprises have a significant impact and a somewhat differential effect on the fixed-income asset classes returns suggests that the surprises should be an important source of information in fund managers' asset allocation decisions.

5 Preliminary Analysis of Portfolio Weights

In this section I provide some descriptive information about the portfolio allocations of different groups of bond funds. The data show that bond fund managers actively change their portfolio allocation and that these changes can cause a shift in the style of the fund. This provides a motivation for using the weights-based approach and a dynamic benchmark based on portfolio weights information.

Table III presents information drawn from the sector portfolio compositions of taxable bond funds for the period of 1997-2006 for different bond style funds. The end of the year observation for each year is considered. The table presents portfolio weights in five asset classes: Government bonds, mortgage, credit, foreign bonds and cash. The figures represent the equal weighted averages across funds of the mean, standard deviation, and the range of portfolio percentage holdings. Table IV and V present a similar analysis for the credit quality and maturity range allocations. For the credit quality allocation I aggregate only for this specific analysis the weights of Govt/Agency with AAA because I am interested in the allocations across different credit ratings. The average standard deviation can be as high as almost 16% for government bond Treasury funds in the government sector, 12% for corporate bond high quality funds in the credit sector, 11.6% for corporate bond high yield funds in the B rating, and 13% for government bond mortgage funds in the long-term maturity range (more than 10 years). Similar to Ferson and Khang (2002), I also present a measure of active portfolio allocation turnover calculated as the average of the sum of the absolute difference of the weights divided by two (Table VI). The past weights are updated with a buy-and-hold strategy. This measure for fund i is therefore the time-series average of:

$$Active\ Turnover_t^i = \frac{1}{2}\sum_{j=1}^{N}\left(|w_{j,t}^i - \tilde{w}_{j,t-k}^i|\right) \tag{7}$$

where $\tilde{w}_{j,t-k}^i$ is defined as in (3) and k in this case is equal to 12 months. The measure should capture the departure of the portfolio's actual weights from the buy-and-hold weights. Almost 15% of the sector portfolio allocation is changed on average in a year. These variations are not explained by a differential in asset classes' performance (captured by the buy-and-hold weights) and may instead suggest timing activity. It is confirmed that the active portfolio allocation turnover is significantly high. On average, the turnover is higher for high yield and multi-sector funds in the credit quality allocation and for government bond general and Treasury funds in the maturity allocation. As mentioned previously, a passive mutual fund manager needs to trade and rebalance the portfolio for various reasons, including changes in the index. For example, the Treasury sector in the aggregate ML index decreased from almost 50% to around 28% during the 1997-2006 period.

Table VI also presents the portfolio allocation turnover for four Vanguard index funds which were in operation during the 1997-2006 period. The active turnover figures suggest that, although bond index funds are considered passive funds, they exhibit significant portfolio changes. Nevertheless, using a Wilcoxon signed rank test, the median fund presents an average portfolio allocation turnover significantly higher than that of the Vanguard Total Bond index in all three allocations. Therefore, although one could think that the scope of style rotation could be limited for managers with a specific objective, it appears that the weights held by funds in the asset classes change to a potentially important extent.

Active fund management involves the reallocation of portfolio weights across assets. This reallocation can cause a drift in a fund's style. As noted by Chan et al. (2002) "Style drift may reflect the manager's attempt to time the style indices. Alternatively, a manager may deviate from his declared style in the hope of recovering from past losses or to follow the crowd and adopt whichever style has been successful". Is there evidence of style drifting in bond mutual funds? Mutual funds have an investment objective assigned by Morningstar that is based on information contained in the fund's prospectus and the manner in which the fund is marketed. Morningstar also provides a category classification based on the underlying securities in the fund's portfolio. According to the Chicago based fund data provider, "Morningstar places funds in a given category based on their portfolio statistics and compositions over the past three years. If the fund is new and has no portfolio history, Morningstar estimates where it will fall before giving it a more permanent category assignment. When necessary, Morningstar may change a category assignment based on recent changes to the portfolio." Finally, Morningstar provides a fixed-income style box with information about the current style of the fund. The criteria used are duration and credit quality. Therefore Morningstar splits fixed-income funds into three groups based on the interest rate sensitivity (high, medium, and low) and into three credit-quality groups (high, medium, and low) for a total of nine possible combinations. Style box assignments for funds are recalculated whenever Morningstar receives updated information on duration and credit quality. In this analysis, I identify the funds that drift from their style as those whose Morningstar category or Morningstar style has changed at least once during their existence.

Table VII shows how many bond funds change category and style and the frequency of the change. Almost 40% of the funds in my sample change category at least once and 76% change style at least once. Moreover, on average they change category more than twice and style more than four times. This suggests that many funds experience time-variation in their exposures to systematic risk factors. This time-variation is confirmed when a conditional performance model is estimated in Section 6.3. There is evidence of time-varying betas for both active and passive (index) funds.[31] In this setting, as explained previously, a traditional returns-based approach (unconditional Jensen alpha that assumes that the systematic risk is constant) is likely to be inaccurate.

6 Results

In this section the results for the CT measure applied to three asset allocation breakdowns (sector, credit quality, and maturity range) are presented first. Second, the decomposition of the abnormal return in CT and return GAP is presented. Third, the results using a returns-based approach are presented. Fourth, the results for the conditional CT are

[31] The results for the index funds are not shown but they are available upon request.

presented. Fifth, the sources of the asset allocation performance are evaluated. Finally, I investigate whether there is any evidence of performance persistence, whether there are any meaningful associations between fund characteristics and performance measures, and whether the return GAP helps to predict future mutual fund returns.

6.1 CT Results

The CT measure as expressed by equation (2) was first calculated. The lagged weight $\tilde{w}^{i}_{j,t-k-1}$ is the previous portfolio weight updated assuming a buy-and-hold strategy. In an untabulated analysis, the CT measure using $k \leq 3$ months (i.e. the past weight is equal to the closest available lagged weight up to the previous quarter) is compared to the measure when $k = 12$ months. By contrast with the findings of Grinblatt and Titman (1993), it appears that abnormal performance is more evident using more recent lagged weights. This is consistent with the idea that the superior information of the manager is quickly incorporated into prices. To maximize the number of observations in the following analyses the closest past weights up to one year in the past ($k \leq 12$) are used. The number of funds range from 634 when considering the credit quality allocation to 751 when considering the sector allocation and to 932 when considering the maturity allocation.

The cross-sectional distribution of the CT measure annualized and in percentage is presented. In particular, as in Jiang et al. (2007) the following statistics are presented: the mean, median, the 25% and 75% quartile and the 5%, 10%, 90% and 95% percentiles. The goal is to test whether there is timing ability for the entire sample and whether there are some funds that have strong positive or negative timing abilities after controlling for sampling variability (luck). Following Kosowski et al. (2006) and Jiang et al. (2007) a bootstrapping approach is used to calculate the p-values. This is important because of the unbalanced nature of the panel of funds and the likely violations of the *i.i.d.* assumption across funds. Since funds can hold similar securities and also considering that fixed-income securities can be highly correlated, cross-fund correlations in abnormal returns should be expected. Moreover, a bootstrapping approach also addresses issues related to the finite sample distribution. The bond index returns are randomly resampled keeping the weights fixed[32]. In each simulation the CT measure is calculated following (2) using the same sequence of resampled index returns for all the funds thereby preserving any cross-sectional correlation. Under the null hypothesis of no timing ability, future returns should not be correlated with past weights. This procedure is repeated 2000 times to obtain the empirical distribution of all the cross-sectional statistics. The bootstrapped

[32] An implicit assumption is that weights, for an uninformed manager, are not chosen based on past returns. This should not be the case for a manager that passively relies on momentum strategies. However, unlike stock returns, corporate bond returns do not display momentum (see Gebhardt et al. 2005). Hence, momentum strategies are unlikely to be popular.

p-values are obtained as follows:

$$p = \frac{1}{J}\sum_{j=1}^{J} I_j$$

where J is 2000, the number of simulations, and I_j is an indicator function with value of 1 if the statistic of the bootstrapped sample j is greater than what is obtained in the estimation. For example, when the cross-sectional mean of the CT is 0.1, then to obtain the associated p-value I counted how many times the cross-sectional mean of the CT obtained using the bootstrapped returns was greater than 0.1.[33] Then, this number was divided by 2000. Therefore, a low p-value (close to 0) implies that the estimated timing measure is consistently higher than its bootstrapped values and thus provides evidence of positive timing ability. By contrast, a high p-value (close to 1) implies that the estimated timing measure is consistently lower than its bootstrapped values and thus shows evidence of negative timing ability.

First, the CT measure is calculated using monthly data. Table VIII panel A presents results for the sector, credit quality and maturity allocations considering all the cross-section of available funds. The question asked here is how skilled is the manager in asset allocation decisions? Different horizon specifications of the CT measure are considered. In particular, I present results considering one-month and three-month returns after the disclosure date if there is no other weight observation. For example, when considering a three-month horizon, if there is a weight observation at the end of December 2000 and a lagged weight observation before December 1999, the weight difference (adjusted for buy-and-hold) is multiplied by the returns of January, February, and March 2001 or up to the month when the next weight is observed if it is before March 2001. Hence, if there is another weight in February, only two months (January and February) are used.[34] Considering all the allocations, both the mean and the median are close to zero. They are positive for the credit and maturity allocations however only the mean for the maturity allocation at one month horizon is statistically significant. If we compare the different horizons, it appears that the timing ability is short-lived. The results for a longer horizon tend to be weaker.[35] This is particularly evident for the maturity allocation. This is consistent with a quick incorporation of the information in the prices.

Mutual funds may constrain their investment policy. For example, a Treasury bond fund may be prohibited from investing in high yield bonds.[36] When the credit quality allocation is considered it makes sense to separately examine subgroups of funds that are

[33] I therefore test whether the mean of the CT is significantly higher than the 2000 averages that were obtained in the simulations. Similarly, for the 95% percentile I test whether it is significantly higher than the 2000 95% percentiles obtained in the simulations. In this way it is possible to control for luck.

[34] This was done to avoid overlapping observations.

[35] Additional analyses show that this is more evident using longer horizons such as 6-month and 1-year.

[36] I found however a group of 171 funds that are not corporate or high yield funds but are nevertheless invested in high yield bonds 20% of the reporting periods. I also found a group of 262 funds that are domestic US bond funds but are invested in foreign bonds 20% of the reporting periods.

allowed to invest in different credit qualities. Table IX (panel A) presents the CT results for three types of corporate bond funds and for multi-sector funds. Significant and positive CT measures are obtained by the corporate bond high yield and multi-sector bond funds for the credit quality allocation. Table IX (panel B) presents the results considering the maturity range allocation.[37] Here, there are no clear restrictions on the maturity of the portfolio coming from the investment objectives. The results for all the investment objectives are therefore presented. The government bond general, government bond treasury, and multi-sector bond funds exhibit significant timing ability.[38] It is important to examine different asset class decompositions. They indeed correspond to different skill sets for a bond mutual fund manager. Also some managers may be more constrained by their prospectus in their asset allocation choices.

Next, the CT measure is calculated using daily returns in the month following the disclosure date. In particular, I consider only announcement days and non-announcement days separately. In this way, the CT measure calculated using all the trading return days can be decomposed into a weighted average of the CT measure conditional on the days with announcements and in the CT measure conditional on the days with no announcements. If the CT measure represents managerial ability one should expect that the superior performance would be earned during announcement days when the signal-to-noise ratio is high. Table VIII panel B presents the cross-sectional distribution of the CT measure considering all trading days and the decomposition with only announcement days and non-announcement days. Only for the mean is the sum of the two components equal to the total CT. The average CT measure is lower when it is calculated during non-announcement days rather than announcement days. For the mutual funds for which the CT is positive, the portion of the excess return attributed to the CT conditional on announcement days is close to 90% for the sector and maturity allocations while it is close to 50% for the credit allocation. This is consistent with the finding that the announcements impact less high yield bonds. Using only announcement days, however, does not change the inference very much. Indeed, I calculated the bootstrapped p-values for the CT obtained using only announcement days and they are similar to the p-values calculated using all trading days.

In order to maximize the number of observations, Weight differences with diverse distances are combined in (2) . Sometimes, the past weight is 12-months ago and sometimes it is one month ago. We could expect that the 12-month weight difference would be larger than the 1-month weight difference. Moreover, the 1-month weight difference should be a more precise measure. To address this issue[39], in an untabulated analysis, instead of

[37] As explained in the appendix, the benchmark ML indices for the maturity ranges change according to the fund's investment objective.

[38] However, these findings should be considered with caution. Indeed, the multiple comparisons problem should be accounted for, since I am repeating the test many times and the tests are not independent.

[39] Under a buy-and-hold null updating with buy-and-hold should reduce the effect of this problem.

doing a simple average of (2), I calculated a weighted average with weights equal to 13 minus the number of months that the weights are in distance from each other divided by the total number of months used. In this way, more weight is given to observations with a 1-month weight difference. The CT measure is smaller in magnitude (since I give more weight to a smaller number) but the significance appears stronger for the maturity breakdown.

Finally, since from an investor's perspective the results for a portfolio of funds are relevant, in an untabulated analysis the CT measure using an equally and value-weighted portfolio of funds was calculated. It is confirmed that the CT measure is very close to zero and that only some groups of funds are able to generate some value timing the credit quality allocation[40].

In summary, there is some evidence that some groups of funds have significant timing ability. Is this also economically significant? The magnitude of the results seems rather small. For example, in Table IX the median CT measure for a high yield fund is 11 basis points whereas the median multi-sector fund CT measure is 15 basis points per year considering a one-month horizon. However, in the context of bond mutual funds, few basis points can make the performance ranking of a fund in its category change significantly. The annual average excess return over short-term Treasuries for the average bond mutual fund is only 156 basis points. Hence, 15 basis points represent roughly 10% of the premium. Moreover, if we look to the 95% percentile of mutual funds, they present a CT measure higher than 100 basis points.

6.2 Return Decomposition: CT and RG

I now turn to the attribution analysis as described in (4) using monthly data. For this exercise, it is important to obtain the best possible proxy of the gross return of the fund. If only the sector analysis is used, two funds with the same sector allocation but different maturity and credit quality exposure are assigned the same proxy for the gross return. The government, mortgage and sector ML indices that match the corresponding sectors have their own credit ratings and average maturities. The ratings and maturities of the fund may be different. I therefore adjust the sector allocation for the credit quality and maturity differences between the fund and the government, corporate and mortgage ML indices. More precisely, the proxy of the gross return for fund i can be constructed for

[40] The inference this time was not based on bootstrapping but rather on a t-test on the time series mean using Newey-West consistent standard errors.

the bond component[41] of the portfolio as follows:

$$
\begin{aligned}
R_i^b = {} & w_i^{gov} R^{gov} + w_i^{mor} R^{mor} + w_i^{cor} R^{cor} + \left(w_i^{govqua} - \tilde{w}_i^{govqua}\right) R^{gov} \\
& \left(w_i^{AAA} - \tilde{w}_i^{AAA}\right) R^{AAA} + \left(w_i^{AA} - \tilde{w}_i^{AA}\right) R^{AA} + \cdots + \left(w_i^{B-} - \tilde{w}_i^{B-}\right) R^{B-} \\
& + \left(w_i^{1-3} - \tilde{w}_i^{1-3}\right) R^{1-3} + \cdots + \left(w_i^{10+} - \tilde{w}_i^{10+}\right) R^{10+}
\end{aligned} \tag{8}
$$

where R is the total return index for a particular asset class, credit quality or maturity, w is the weight provided by Morningstar for the fund, and $\tilde{w}$ is the credit quality and maturity weight implied from the fund's allocation in the 3 main ML indices (government, mortgage and corporate).[42] To make a concrete example, assume that there are two funds X and Y that have the same allocation: 50% Treasury and 50% corporate but Fund X has corporate AAA quality whereas Fund Y has A quality. Therefore the credit quality allocation for fund X is $w_x^{govqua} = \frac{1}{2}$ and $w_x^{AAA} = \frac{1}{2}$ and for fund Y is $w_y^{govqua} = \frac{1}{2}$ and $w_y^{A} = \frac{1}{2}$. Let's ignore for simplicity the maturity of the portfolio. Assume that the ML corporate index used to match the corporate sector has AA quality[43]. Then since the allocations in Treasury and corporate of fund X and Y are the same this implies that $\tilde{w}^{govqua} = \frac{1}{2}$ and $\tilde{w}^{AA} = \frac{1}{2}$ for both fund X and Y. Therefore, I need to adjust the fund X for the excess exposure to higher quality and fund Y for the excess exposure to lower quality. According to (8) the benchmark return for fund X and Y will be equal to

$$
\begin{aligned}
R_x^b &= \frac{1}{2} R^{gov} + \frac{1}{2} R^{cor} + \frac{1}{2} R^{AAA} - \frac{1}{2} R^{AA} = \frac{1}{2} R^{gov} + \frac{1}{2}\left(R^{cor} + \left(R^{AAA} - R^{AA}\right)\right) \\
R_y^b &= \frac{1}{2} R^{gov} + \frac{1}{2} R^{cor} - \frac{1}{2} R^{AA} + \frac{1}{2} R^{A} = \frac{1}{2} R^{gov} + \frac{1}{2}\left(R^{cor} + \left(R^{A} - R^{AA}\right)\right)
\end{aligned}
$$

Table X presents the return decomposition results. The number of funds with at least 12 weight observations is now 683 because I lose some funds for which I do not have data available for the credit quality and maturity allocations. I present the results forming an equally weighted portfolio of funds and a value-weighted portfolio of funds. To ensure there are no missing values in the time series, a 12-month horizon is used. The mean and the median of CT are positive but very close to zero consistent with the previous results. However, the return GAP is significantly positive and seems more important than CT in the decomposition. On average, considering both an equally and value weighted portfolio of funds, active managers generate gross returns of 1% over the benchmark portfolio constructed using past holdings. There are also some cross-sectional variations for example corporate high yield funds generate a gross returns of 2% over the

[41] In the analysis I extended the sector allocation to also include the portfolio weights in stocks, preferred, and convertible bonds. The average portfolio allocation in these three asset classes is respectively 0.9, 0.5, and 0.5. These asset classes are matched to an index as described in the appendix.

[42] *gov* stands for government, *mor* stands for mortgage, *cor* stands for corporate, *govqua* stands for government credit quality.

[43] In reality, the credit quality allocation of the ML corporate bond index in the most recent period is 0.5% AAA, 14% AA, 40% A, 22% BBB, 0.8% BB, 0.9% B, 0.1% CCC. To construct the benchmark I used all this information and took into account the time-variation of the weights in the index.

benchmark. For the extent that in the high yield sector more valuation inefficiencies and opportunities are present one could expect managers to exploit them. I also present the return GAP after subtracting expenses and transaction costs that can be compared with the Jensen alpha. The return GAP measures post expenses and transaction costs are higher (closer to zero) than the negative and statistically significant alphas found in the literature. This finding is more evident when considering subgroups of funds such as corporate high yield, corporate bond general, Treasury and multi-sector funds for which the return GAP after expenses and transaction costs is positive (although not statistically significant). On average mutual funds delivered net returns approximately the same as the gross returns of their characteristic benchmarks. This suggests that mutual fund managers hold securities that outperform their benchmarks by almost enough to cover their expenses and transaction costs (on average around 1.3 percent per year, considering 0.8 percent of expenses and 0.5 percent of transaction costs).

Figure 3 shows the annual variations in the average return GAP for an equally-weighted portfolio of the 683 bond funds. For eight out of ten years the return GAP is positive. The highest return GAP was experienced in 2002 with an annualized return of almost 2.5%. There are two negative returns GAP in 1999 and 2005. The year of 1999 was the worst performing year for bond mutual funds. Indeed, an equally-weighted portfolio of the existing bond mutual fund delivered an annualized net return of only 0.2%.

One concern is window dressing. This is the practice of buying and selling securities at the end of a disclosure period for the purpose of providing an inaccurate representation of the holdings of the funds. For equity mutual funds this consists of selling poor performing stocks and buying recent winners[44]. For bond funds, Morey and O'Neal (2006) found some evidence that corporate bond funds increase the holdings in government bonds and decrease the holdings in AAA bonds during disclosure periods. To test whether this can bias the return GAP measure three analyses were performed.

I first use daily mutual fund price returns as in Morey and O'Neal (2006).[45] Jensen's alpha regressions were performed, as in Section 6.3, regressing daily mutual fund price returns on the excess returns of six indices (Treasury, mortgage, investment grade corporate, high yield corporate, foreign bond and S&P500) including dummy variables that interact with the betas. These dummy variables are equal to 1 for the 10 days surrounding the reporting periods. The SEC requires funds to disclose their holdings on their fiscal year-end and six months after that. I test whether the dummy variable associated with the additional exposure to Treasury during reporting periods is significant and pos-

[44] There is only weak evidence of window dressing for equity pension funds (see Lakonishok et al. 1991) but the evidence is stronger for equity mutual funds (see Meier and Schaumburg, 2006) and money market funds (see Musto 1999).

[45] Price returns instead of total returns were used for problems related to the reporting of the daily NAV for bond funds.

itive. In a sample of 636 funds for which I have daily data from 2001, Only 32 funds were found to have a T-statistic greater than 1.96 associated with the Treasury interaction term. This is approximately 5% of the total number of funds. Moreover, among these funds only 18 funds (2.8%) also have a significant reduction in the exposure to the mortgage or investment grade corporate without having a significant increase in the exposure to other asset classes (high yield corporate, foreign bond and S&P500) during the reporting periods. By random chance we could expect that some funds will exhibit a significant estimate. Taking out these funds does not affect the results.

Second, a subgroup of funds that reports more frequently is separated. There are 226 funds that report at least 6 times per year since the end of 2003. These funds exhibit an annualized return GAP of 1.3%. The remaining funds exhibit an annualized return GAP of 1% which is not statistically different from 1.3%.

Third, the return GAP of an equally weighted portfolio of funds is regressed on monthly dummies. This is to test whether the return GAP is different around the most common disclosure months. The fiscal year-end is most common in September, October, and December (see Table XI). Therefore I used a dummy for these months and for 6 months later (March, April, and June). I also consider the following month because in the return GAP the benchmark uses the lagged weights. The results suggest that the dummies are not significant whereas the intercept is still positive and statistically significant (Table XI).

Another concern is whether there is some residual risk exposure in the return GAP maybe due to the trade occurred after the disclosed weights or to the investment in securities with different risk-return characteristics than the securities in the indices. To control the former, I test whether the return GAP is correlated with any risk or style factors. Accordingly, the return GAP is regressed on the excess returns of six indices (Treasury, mortgage, investment grade corporate, high yield corporate, foreign bond and S&P500). No evidence of significant loadings is found and the intercept is positive and statistically significant.[46] To address the latter concern - that the return GAP is due the investment in securities that have a different systematic risk than the securities in the indices - the adjusted R-squared from a regression of mutual fund excess returns on the excess returns of the above six indices is calculated. The average adjusted R-squared for all the funds considered for the return GAP is 84% while the median is 90%. Therefore, it seems that the majority of the funds have little residual risk. Moreover, if I calculate the return GAP for an equally-weighted portfolio of funds with below median adjusted R-squared, the return GAP is equal to 1.19% not statistically different from the funds with above median adjusted R-squared.

[46] I also tried to exclude 106 funds that invest in equity and preferred stocks with a combined average allocation of more than 1%. The average return GAP of the remaining funds is very similar to the total sample (1.02%).

The analysis so far suggests mild and short-lived evidence of timing ability that is limited to some groups of funds timing the credit quality and maturity allocation. The average mutual fund does not exhibit timing ability but it also does not exhibit negative timing ability as found in the literature. The findings on the return GAP measure suggest that selectivity can be an important component of performance. Return gap could also reflect the benefits of timing that operates at a higher frequency than the frequency of the observed weights. This provides a more optimistic picture about bond mutual fund performance than what has been documented in the existing literature.

6.3 Returns-based Measures

At this point, the results appear more optimistic than what has been found in previous literature using a returns-based approach. Both approaches (the weights-based and the returns-based) provide relevant tools to investigate the mutual fund performance. Whereas the focus of the weights-based approach is the investment ability, that can be better studied examining the performance before fees and costs, the focus of the returns-based approach is to test whether there is any value added for the investors after the fees and costs are subtracted from the returns. To complete the study it is important therefore to estimate returns-based performance measures using the same observations as in the previous analysis. (Using all the data available provide qualitatively similar results.)

First, following Blake et al. (1993) and Elton et al. (1995) bond portfolio excess returns are regressed on the excess returns of six indices (Treasury, mortgage, investment grade corporate, high yield corporate, foreign bond and S&P500). I use both an equally-weighted and value-weighted portfolio of all funds and of funds grouped by investment objective. To conserve space only the results with an equally-weighted portfolio are presented. Table XII panel A provides evidence that the unconditional model delivers negative and significant alphas. Since groups of funds specialize in particular asset classes, the number of indices for funds with a particular investment objective is reduced. For example, since high yield funds generally do not invest in Treasury and mortgage securities I exclude these indices from the regression. For Treasury funds three Treasury indices with different maturity ranges (1-3 year, 5-7 year and more than 10 year) are considered.

I estimate a conditional model following Ferson and Schadt (1996) using the instrumental variables discussed previously. The mortgage spread is not used because it does not appear to be significant in the regression. The conditional alphas are in general lower than the unconditional ones (see panel B). The only exception is for high yield funds where the alphas look better in the conditional model (similar to the evidence for equity mutual funds), but are still significantly negative. There is evidence of time-varying betas because the interaction terms enter significantly into the regression. Indeed, the F-test indicates that the null hypothesis that the coefficients on the interaction terms are equal to zero is rejected. The results are confirmed using a value-weighted portfolio although the alphas appear to be closer to zero. In an untabulated analysis I follow Christopherson et al. (1998) by specifying the conditional alphas as a linear function of the predetermined information. An F-test is performed to evaluate whether the alphas are time-varying. For some investment objectives, alphas are time-varying. Indeed, some interaction terms enter significantly into the regression model. The alphas however still appear to be negative and statistically significant for the majority of the investment objectives.

Furthermore, in an untabulated analysis, I estimated quadratic regressions following the method proposed by Treynor and Mazuy (1966) including the squared excess return of the benchmark portfolio as an additional regressor. The timing coefficients on the squared terms for all the mutual funds are not significant with the exception of a significant negative coefficient for the value-weighted portfolio for the equity index. Finally, a Sharpe (1992) Style Analysis[47] is performed using the same indices used in the Jensen alpha regression with the addition of the cash index (3-month T-bill). In this way the estimated portfolio weights can be compared with the average actual portfolio weights. This untabulated analysis shows that the excess returns (average differences between the mutual fund returns and the benchmark returns constructed using the estimated portfolio weights) are very similar to the unconditional Jensen alpha. For the average fund the excess return is negative and significant. Looking to the portfolio weights we note some differences. The estimated weights appear to overweight the cash exposure and underweight the mortgage exposure. Since cash delivers on average lower return than other investment positions this could partly explain some of the differences between the return GAP and the Jensen alpha.

6.4 CCT Results

Table XIII presents the results for the CCT measure (6). The results using monthly data for a one-month horizon are presented. The CCT measure is compared with the unconditional CT measure. The unconditional measure is slightly different from what I previously estimated because I used the returns in excess of the historical average following Ferson and Khang (2002). The instrumental variables are the same as what was used in the conditional returns-based analysis. Following Ferson and Khang (2002), the lag of the index return is also included. The procedure to estimate the CCT is as follows: First, I run a regression of index returns which match the asset classes on conditional

[47] This consists of estimating the portfolio weights in each asset class using a quadratic programming problem that minimizes the square of the tracking errors under the non-negative constraint on the weights and the constraint that the sum of the weights is one.

information and I save the fitted coefficient vector. Then, I calculate the CCT as the time-series mean of (6) using the saved fitted values as estimates of the conditional expected return. The CCT measure appears to be similar to the unconditional measure. Similar results are obtained using daily return data. The difference between the unconditional and the conditional CT measure is an estimate of $\sum_{j=1}^{N} cov\left[w_{j,t-1}, E\left[R_{j,t}|Z_{t-1}\right]\right]$, the second term on the right-hand side in the decomposition (5). This term captures the component of performance which is attributable to mechanical trading based on public information. The average and the percentiles of this difference appear to be very small. This finding appears to be similar to what was found for pension funds by Ferson and Khang (2002) and contrasts with the result that betas are correlated with lagged public information.

6.5 Sources of the Asset Allocation Performance

One advantage of using weights information is that it is possible to study the main drivers of the abnormal return. I want to test whether weight changes in each asset class provide valuable information about future returns. I carry out a test that is similar to Graham and Harvey (1996) but focusing only on the largest weights increase and decrease. These decisions should be the most informative about the managers' predictions. Accordingly, I calculate the average monthly returns in excess of the risk-free rate in the month following the largest weight increase and the largest weight decrease separately. Then, I equally-weight across funds for which I have at least 5 monthly observations of weight increases and decreases. Table XIV presents the results for the different portfolio allocation breakdown. These results are not directly comparable with the previous CT results because the number of funds is different and the performance is not aggregated across asset classes. It seems that a small group of bond fund managers on average correctly anticipate the direction of the international bond market. Another group of fund managers incorrectly anticipate the future returns of the other sectors. For the maturity breakdown there is some predictability of returns related to long-term bonds (more than 10 years). Indeed, the average return following a weight increase is significantly higher than the return following a weight decrease. Finally, for the credit analysis at the aggregate level there is some evidence of significant ability for AAA bonds and B rated bonds. Examining across different fund styles (not shown in the table) the managers who are specialized in the corporate sector such as high yield and corporate general mutual funds appear to correctly anticipate the future returns of the lowest rated non-investment grade bonds.

6.6 Performance Persistence and Panel Data Analyses

First, I test whether there is any evidence of persistence in the timing ability and return GAP measures. Funds used in Table X are sorted into quintiles according to their averaged lagged CT and return GAP measured over a one-year and two-year period.[48] Then, I compute the average CT and return GAP during the subsequent month, quarter, and year by weighting all funds in each quintile equally. Table XV presents these results using two ranking periods (the previous year and the previous two years) and three different holding periods (one-month, one-quarter, and one-year). Funds in the worst performing CT quintile exhibit a negative CT measure while funds in the best performing CT quintile exhibit a positive CT measure in the subsequent year. This difference is of the order of 64 basis points per year and statistically significant considering one-quarter holding period (panel B). However, this is not more significant considering one-year holding period. For the return GAP measure the magnitude of the spread portfolio is larger, of the order of 1.6 and 1.3 percent per annum considering respectively one-month and one-quarter holding period. The 1.3 percent is marginally significant.[49] This evidence is weaker if I consider one-year holding period. Indeed, there is no evidence of significant persistence when considering a one-year period and the average spread portfolio is only 55 basis points for the return GAP. In summary, it appears that the performance persistence is short-lived.

Second, I perform a panel data analysis. The goal is to investigate whether some fund's characteristics are associated with the CT and GAP measures and try to better understand the findings of lack of long-term persistence. I regress the Characteristic Timing and Return Gap measures on fund characteristics to examine which fund characteristics are associated with large or small measures. The fund and portfolio characteristics considered are the log of Total Net Asset (TNA), the percentage of cash in the portfolio, the duration of the portfolio, the average credit quality of the portfolio, the turnover rate, the log of the age of the fund (expressed in years), the yield of the fund's distributions, the expense ratio, the Morningstar rating, the past alpha calculated by Morningstar, the net flows, and the previous year's volatility of flows. Net flows for fund i are calculated using the TNA difference between two consecutive months (or quarters) adjusted for the return of the fund[50]:

$$Flows_t^i = \frac{TNA_t^i - TNA_{t-1}^i\left(1 + Rp_t^i\right)}{TNA_{t-1}^i}$$

[48] I used quintiles instead of deciles because at the beginning of the period the number of funds is not very large.

[49] Considering one-month horizon it appears that there are some outliers. Indeed, if a Wilcoxon signed rank test for zero median of the return GAP on the 5-1 Quintile portfolios is performed, the associated p-values are 0.049 for 1-year past window and 0.036 with 2-year past window,

[50] The flows data are Winsorized at the top and bottom 1% because these outliers are likely caused by mergers. The monthly TNA information is obtained by CRSP.

Table XVI shows the results for the 12-month horizon using as dependent variables the raw return GAP measure, the return GAP measure after transaction costs, and after transaction costs and expenses[51]. I present two different specifications of the regression. The first specification is with both fund-fixed effects and time dummies. This specification is best suited to capture time-series effects of variables that have significant time-series variations (for example TNA and flows). The second specification includes only time-fixed effects. In this case I focus on the explicative power of the cross-section and it is suitable for variables that have little time-series variation and large cross-sectional variations (for example expenses). Considering the first specification, I find that the return GAP is negatively associated with the size of the fund. Smaller funds tend to exhibit higher return GAPs. This suggests some diseconomies of scale also documented by Chen et al. (2004) for equity funds. This result is also consistent with Berk and Green's (2004) model and sheds light on the lack of persistence in the return GAP measure[52]. One could expect that the effect of size could be particularly important for high yield funds considering the lack of liquidity in the low-rating corporate bond market. Indeed, when the TNA is interacted with a dummy for high yield funds this interaction term comes out negative and statistically significant. I also find that funds which experienced large flows (especially lagged one quarter) and past volatility of flows tend to exhibit smaller return GAP measures. This result mirrors what has been found in the equity literature (see Ferson and Warther 1996 and Edelen 1999) and it is consistent with a lack of persistence in the performance measures.

I also find a significant positive relationship between the average turnover and the return GAP measure. As pointed out by Kacperczyk at al. (2008) the return GAP should be negatively related to the hidden costs and positively related to the hidden benefits of a mutual fund. The results show that turnover is positively associated with the return GAP. This is partly associated with the presence of trading costs. Considering the return GAP measure after transaction costs the relationship between the return GAP is weaker although still positive and marginally significant. This could suggest that interim trades create sufficient value to cover the transaction costs. Funds that report high income yields in the form of distributions are associated with a lower return GAP. A similar finding was also documented by Chen et al. (2006). One explanation is that some bond funds invest in high yields bonds which may have higher default probability that can hurt the ex-post performance. Indeed, this effect seems to be present in high yield funds as suggested by the interaction of the distribution yield with the high yield dummy. The return GAP is also positively associated with the Morningstar rating and past alpha.

Considering the second specification with only time-fixed effects, funds that have

[51] The results for 3-month horizon are qualitatively similar.

[52] For the Berk and Green (2004) model to work we also need investors to chase past performance. This has been shown for bond mutual funds by Zhao (2005).

a portfolio with higher duration and lower credit quality have a higher return GAP.[53] Expenses are positively associated with the return GAP. The relationship with the return GAP after expenses and transaction costs is close to zero. This suggests that managers are able to earn back their fees and this contrasts with the findings of Blake et al. (1993) of a negative and close to one coefficient in the regression of alphas on expenses (a percentage-point increase in expenses leaded to a percentage-point decrease in performance).

The CT measure results show some differences relative to the return GAP measure (see Table XVII). Some differences are expected since it is known that a fund with positive timing ability can exhibit negative ability and the return GAP is positively associated with alpha. The size of the fund appears to be positively associated with the CT measure. This suggests that maybe only large funds have the ability and expertise to engage in timing activity across different sectors. The holdings of cash are negatively associated with the CT measure. The same type of association is also found with the Morningstar rating. This can be due to the negative alpha assigned to timing ability and to the fact that timing activity can push a fund into another style box and change the group of funds that is compared with. Finally, the relationship between flows and volatility of flows and the CT measure is not significant.

Finally, I examine whether the return GAP can help an investor to choose better performing funds. So far I showed that the return GAP after expenses and transaction costs provides more favorable evidence of performance (it is closer to zero) compared to standard performance tests. The relevance of this finding could be undermined if traditional tests help to predict future fund performance better than tests based on weights-based measures. To examine this question, bond mutual funds are sorted in quintiles based on average past year and two-year performance measured using alpha and the return GAP. The returns and risk-adjusted returns of an equally-weighted portfolio of the funds in each quintile are calculated during the subsequent month. The risk-adjusted returns are measured using an unconditional Jensen alpha. Table XVIII panel A shows the results using alpha as sorting criterion. Funds with the most favorable alphas (fifth quintile) deliver an annualized 0.9 percent return and 1.3 percent risk-adjusted return more than funds with poor past return GAP (first quintile). However, if an investor uses the past return GAP as sorting criterion she would obtain a 2.3 percent return and 1.9 percent risk-adjusted return. The average of the return GAP based portfolio five minus one is higher than the average of the alpha based portfolio five minus one with a p-value of 5.5%. These findings are similar when the portfolios are sorted based on the past two-year performance rather than the one year performance.

[53] This may suggest that these funds load to some risk factors. However, when a regression of return GAP on the excess returns of several bond indices is performed, a positive and significant intercept is still found.

7 Conclusion

This paper presents a weights-based analysis applied to bond mutual fund performance. A novel data set of portfolio weights from 1997 to 2006 is used. This information is used to test the timing and selectivity ability of bond mutual funds. The timing ability is defined as the ability to increase (decrease) the portfolio investment on the asset class which is more likely to perform better (worse) during the next month or few months. This provides indirect evidence that mutual fund managers have superior information (or at least use better models than unsophisticated investors) concerning future macroeconomic developments and their impact on bond returns. I consider three different portfolio allocations: a sector allocation, a credit quality allocation, and a maturity allocation.

Using a sample of almost one thousand U.S. bond mutual funds I document that managers engage in considerable trading activity. Part of this trading is due to changes in the characteristics of bonds and in part due to active strategies. These strategies include the reallocation of portfolio weights across different asset classes and characteristics. However, the findings indicate that on average there is little evidence of timing ability and only a subgroup of bond funds presents timing ability particularly related to the credit quality and maturity asset allocation decisions. The timing ability appears to be short-lived especially for the maturity allocation. Upon examination of different investment objectives, it seems that some funds are good in some allocation decisions but not in others, suggesting a skill specialization for different investment objectives. For example, corporate high yield funds create some value by changing the credit quality allocation but not by changing the sector and maturity allocation. The multi-sector funds appear to be the timers among bond funds. They successfully change the credit quality and maturity allocation. Other funds such as general government, mortgage and Treasury funds are successful in timing the maturity allocation. These results are confirmed when using a conditional model. The excess returns due to timing activity appear to be realized mostly during macroeconomic announcements which are days with high signal-to-noise ratio. An analysis of the source of the asset allocation performance also reveals that bond funds were successful in timing the foreign sector, AAA corporate bonds, and low (B) quality corporate bonds. For the maturity breakdown there is some predictability of returns related to long-term bonds (more than 10 years).

I provide some evidence of timing ability across different fixed-income asset-classes and characteristics, but it does not appear to be significant for the average fund. It is possible that similar agency and behavioral considerations, which negatively affect the fund's performance, found by Chan et al. (2002) could also be present in bond funds. For example, it is different if a bond mutual fund manager changes style for timing reasons or to try to recover from past losses or to follow the crowd. Further research could investigate this conjecture.

The weight information is also used to construct a dynamic benchmark which is specific to each fund. The mutual fund return is compared to a passive benchmark, which is calculated using past weights. This benchmark is able to better capture time-variation in risk exposure than the traditional fixed-beta regression. This performance measure called return GAP captures a selectivity component and hidden benefits due to interim trading. The return GAP is compared to the traditional alpha and to the conditional alpha. While using a returns-based approach, a negative and significant alpha is obtained. Using a weights-based approach, the return GAP after expenses and transaction costs is close to zero and is significantly positive before expenses and transaction costs (on average equal to 1% per annum). This provides evidence that mutual fund managers have investment ability holding securities that outperform their benchmarks by almost enough to cover their expenses and transaction costs.

A persistence test based on sorting the funds in quintiles based on past performance shows no evidence of significant performance persistence in the following year, although there is evidence of persistence in the following quarter. Panel data analyses show that this could be consistent with the presence of diseconomies of scale as suggested by the Berk and Green (2004) model. Indeed, large funds exhibit a small return GAP measure. The return GAP measures are also negatively affected by past flows and flows' volatility. Turnover rate is instead positively associated with the return GAP measure. Bond funds that trade more often are successful in creating some value with the trading. Bond fund managers also appear to be able to earn back their fees. Whereas Blake et al. (1993) found a negative and one-to-one relation between expenses and performance, I found that this relation is positive and significant before fees and insignificant after fees. Therefore, the conclusion of Blake et al. (*ibid.*) to invest in low cost bond funds does not apply to this sample. Concerning the portfolio characteristics, funds with a portfolio of lower credit quality and high duration are associated with a larger GAP measure. The return GAP is also positively associated with past alpha and Morningstar ratings. This does not appear to hold for the CT measure.

In conclusion, this paper provides a more optimistic picture about active management in the fixed-income market relative to the returns-based approach used in the existing literature. A weights-based approach complements what is captured by the returns-based approach providing a more complete picture of the performance. I also document that for an investor it can be important to use the return GAP measure to predict future fund performance since it provides a more precise signal than Jensen's alpha. Consistent with the efficient market hypothesis, it is however difficult to find evidence of superior performance and value added for investors. However, bond funds exhibit managerial ability before fees and expenses are subtracted from the returns. Consistent with the equilibrium model of Grossman and Stiglitz (1980) and Berk and Green (2004), fund managers beat their benchmarks by almost enough to cover fees and expenses.

Appendix

Portfolio allocations

Morningstar provides four different asset allocation breakdowns of the fund's portfolio holdings. Table 1 presents these analyses. These data are obtained from voluntary surveys sent to mutual funds and from portfolio information submitted by the funds. The broadest classification consists of portfolio weights for bonds, stocks, preferred stocks, convertibles bonds, foreign bonds and other securities.[54] Portfolio weights are also reported for more narrow sectors. A sector analysis is provided which includes portfolio weights from five sectors: US government bonds, mortgage, credit, foreign, and cash. Unfortunately, before 2004, only annual historical portfolio weights were reported. The annual figures reflect the last data received from a fund for each calendar year. These annual data have been used by Comer (2006) in his analysis of general government bond funds. Another analysis provided by Morningstar is the credit quality allocation, which depicts the quality of bonds in the portfolio. It shows the percentage of fixed-income securities that fall within each credit-quality rating as assigned by Standard & Poor's or Moody's.[55] These data are acquired by Morningstar through a quarterly survey that the Chicago based company distributes directly to the funds. The quarterly dates are the end of March, June, September and December. However, many bond funds report the credit analysis of the data once or twice a year. Finally, a maturity allocation is reported by Morningstar. This analysis consists of the percentage of bonds in the portfolio that fall within the maturity ranges listed in Table 1. The average effective maturity and the average duration of the fund's portfolio are also provided. Table 2 shows the number of funds and observations for each year. In the most recent period the frequency of the data improved.[56]

[54] In the analysis I do not consider other securities and I reweigh the weights to sum to 100%. I exclude funds which present a weight in other securities greater than 50%.

[55] I also did not consider the non-rated/unavailable allocations and I reweigh the weights to sum to 100%.

[56] In cases where the portfolio weights do not change from one period to another, I assume that it is stale information and I delete these records. This problem is more frequent for the credit allocation where I eliminate almost 20% of the observations.

Broad portfolio composition (as % of total assets)	Sector allocation (as % of bonds & cash)	Credit quality allocation (as % of bonds)	Maturity range allocation (as % of bonds)
Cash	US Govt.	US Govt. and Agency	Less than 1 Year
Stocks	Mortgage	AAA	1-3 Year
Bond	Credit	AA	3-5 Year
Preferred Stocks	Foreign bonds	A	5-7 Year
Convertible bonds	Cash	BBB	7-10 Year
Foreign bonds		BB	10-15 Year
Other		B	15-20 Year
		B-	20-30 Year
		Not rated or unavailable	

Table 1: Morningstar portfolio analysis

	1997		1998		1999		2000		2001	
	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights
Broad portfolio composition	937	3.997	940	3.583	872	3.562	811	4.137	772	4.569
Sector allocation	482	1.000	557	1.000	551	1.000	563	1.000	582	1.000
Credit quality allocation	782	2.955	792	2.622	771	2.437	720	2.026	699	2.332
Maturity range allocation	809	1.800	902	2.392	839	3.237	798	4.006	758	4.636

	2002		2003		2004		2005		2006	
	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights	# Funds	# Weights
Broad portfolio composition	704	4.773	678	6.389	655	5.663	610	5.264	576	4.347
Sector allocation	589	1.000	597	1.007	594	5.424	559	5.263	525	4.171
Credit quality allocation	589	1.324	643	2.249	563	3.025	503	2.618	468	2.314
Maturity range allocation	685	1.734	668	6.100	644	5.638	602	5.209	569	4.320

Table 2: Number of funds and average number of portfolio weights records per year for different allocations

Bond indices

To calculate the performance measures I need to match each asset class to a bond index. Data on the Merrill Lynch (ML) bond indices total returns (income, price appreciation and paydown return) were obtained by Bloomberg. They are available from the beginning of 1997. Table 3 provides a list of the bond indices used for each asset class. For the maturity ranges, the ML Treasury indices were used for Treasury funds, the BBB indices for the high-yield funds, and the aggregate indices for the remaining funds. I obtained daily data for all the indices except for preferred and convertible indices for which only monthly data were available.

Bond index abbreviation	**Full name**	**Asset class**
MLTBill	Merrill Lynch T-bill index	Cash or maturity less than one year
MLAGG	Merrill Lynch Aggregate bond index	Bond
MLTRE	Merrill Lynch Treasury index	Government
MLMORT	Merrill Lynch Mortgage index	Mortgage
MLCOR	Merrill Lynch Corporate index	Credit
MLTREAG	Merrill Lynch Treasury and Agency index	Government and Agency
MLCORAAA	Merrill Lynch Corporate AAA index	Credit AAA
MLCORAA	Merrill Lynch Corporate AA index	Credit AA
MLCORA	Merrill Lynch Corporate A index	Credit A
MLCORBBB	Merrill Lynch Corporate BBB index	Credit BBB
MLCORBB	Merrill Lynch Corporate BB index	Credit BB
MLCORB	Merrill Lynch Corporate B index	Credit B
MLCORCCC	Merrill Lynch Corporate CCC index	Credit B- and Not rated
MLHY	Merrill Lynch High Yield	Credit below BBB
MLTRE13 MLAGG13 MLBBB13	Merrill Lynch Treasury 1-3 Year Merrill Lynch Aggregate 1-3 Year Merrill Lynch BBB 1-3 Year	Maturity 1-3 year
MLTRE35 MLAGG35 MLBBB35	Merrill Lynch Treasury 3-5 Year Merrill Lynch Aggregate 3-5 Year Merrill Lynch BBB 3-5 Year	Maturity 3-5 year
MLTRE57 MLAGG57 MLBBB57	Merrill Lynch Treasury 5-7 Year Merrill Lynch Aggregate 5-7 Year Merrill Lynch BBB 5-7 Year	Maturity 5-7 year
MLTRE710 MLAGG710 MLBBB710	Merrill Lynch Treasury 7-10 Year Merrill Lynch Aggregate 7-10 Year Merrill Lynch BBB 7-10 Year	Maturity 7-10 year
MLTRE10+ MLAGG10+ MLBBB10+	Merrill Lynch Treasury 10+ Year Merrill Lynch Aggregate 10+ Year Merrill Lynch BBB 10+ Year	Maturity 10-30year
FOREIGN	Value weighted index of 3 Merrill Lynch indices: Global Government Index II, Excl US; Global non sovereign excluding USD; Global Emerging Market Sovereigns Plus	Foreign bond
S&PCOMP	Standard & Poor's 500 Index	Stock
PREF	Merrill Lynch Preferred Index	Preferred
CONV	Merrill Lynch Convertible Index (all qualities)	Convertible

Table 3: Bond indices and matched asset classes

Macroeconomic announcements

The final data set includes data from the 22 macroeconomic announcements listed in Table 4. The total number of announcements is more than 2700. These are generally released monthly except for initial jobless claim (released weekly) and a few other indicators released at a lower frequency (Employment Cost Index, FOMC interest rate decision, Nonfarm Productivity and Unit Labor Costs). The economic indicators considered in this study tend to be released during the second half of the week. Often the day of the announcement coincides with other announcements. This always happens for a few announcements that are released at the same time. These are Non-farm Payrolls and Unemployment rate, Capacity Utilization and Industrial Production, GDP and GDP Deflator, and Non-farm Productivity and Unit Labor Cost.

Announcements name	**Release Frequency**	**Source**
Advance retail sales	Monthly	Bureau of the Census
Capacity Utilization	Monthly	Federal Reserve Board
Change in Nonfarm Payrolls	Monthly	Bureau of Labor Statistics
Chicago Purchasing Manager	Monthly	Institute for Supply Management
Consumer Confidence	Monthly	Conference Board
Consumer Price Index Less Food and Energy	Monthly	Bureau of Labor Statistics
Employment Cost Index	Monthly	Bureau of Labor Statistics
Existing Home Sales	Quarterly	Bureau of the Census
Federal Open Market Committee rate decision	8 per year	Federal Reserve Board
Gross Domestic Product	Monthly	Bureau of Economic Analysis
GDP Price Deflator (advance, preliminary and final)	Monthly	Bureau of Economic Analysis
Housing starts	Monthly	Bureau of the Census
Industrial Production	Monthly	Federal Reserve Board
Initial Jobless Claims	Weekly	Bureau of Labor Statistics
NAPM (after 1/02 ISM Manufacturing)	Monthly	Institute for Supply Management
New Home Sales	Monthly	Bureau of the Census
Nonfarm Productivity	8 per year	Bureau of Labor Statistics
Philadelphia Fed	Monthly	Federal Reserve Bank of Philadelphia
Producer Price Index Less Food and Energy	Monthly	Bureau of Labor Statistics
Trade Balances-Goods and Services	Monthly	Bureau of Economic Analysis
Unemployment Rate	Monthly	Bureau of Labor Statistics
Unit Labor Costs	8 per year	Bureau of Labor Statistics

Note: The Institute for Supply Management was called National Association of Purchasing Management before 2002

Table 4: US Macroeconomic announcements

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Table I

Statistics of U.S. Taxable Bond Mutual Funds (1997-2006) and Aggregate Bond Indices

This table reports summary statistics for the sample of U.S. taxable bond mutual funds and for different investment objectives provided by Morningstar. The statistics are calculated across time and then averaged (for total net assets summed) across funds. Total net assets are summed across share classes of the same fund and the other characteristics are value-weighted across the share classes. As benchmarks, a portfolio of bond index funds and bond ETFs, and the Vanguard Total Bond Index fund are included. The mean and the standard deviation of the Lehman and Merrill Lynch Aggregate bond indices are also presented.

	No. of Funds	No. of Share Classes	Tot. Net Assets (bill.)	Expense Ratio	Return Mean (%/year)	Return Std. Dev. (%/year)
All active funds	969	3536	626.420	0.821	5.255	4.014
Corp. Bond High Yield	148	634	110.470	1.057	5.123	7.416
Corp. Bond General	322	1149	235.753	0.765	5.374	3.510
Corp. Bond High Quality	157	524	76.913	0.687	5.161	2.872
Govt. Bond General	163	602	70.433	0.828	5.016	3.167
Govt. Bond Mortgage	72	257	68.957	0.759	5.168	2.443
Govt. Bond Treasury	38	90	21.457	0.635	5.859	5.279
Multi-Sector Bond	69	280	42.438	1.037	5.522	4.618
Bond Index Funds and ETF	32	58	52.365	0.333	5.673	4.114
Vanguard Tot. Bond Index	1	3	23.391	0.209	5.866	3.539
Lehman Aggregate Bond Index					6.129	3.564
Merrill Lynch Aggregate Bond Index					6.158	3.608

Table II

Taxable Bond Mutual Funds Turnover Rate Compared to Equity Mutual Funds (1997-2006)

This table reports the turnover rate of bond mutual funds for different investment objectives, of a portfolio of bond index funds and bond ETFs, of the Vanguard Total Bond Index fund, of equity mutual funds, and of the Vanguard 500 Index fund. The turnover rates are averaged across time and then averaged across funds. The turnover rate is defined as the lesser of purchases or sales (excluding all securities with maturities of less than one year) and dividing this by average monthly net assets. The turnover rate for equity mutual funds is calculated over the 1997-2006 period for a sample of 1785 active equity mutual funds obtained from CRSP with TNA greater than 15 million and one year of reported returns.

	Turnover rate
All active funds	150.06
Corp. Bond High Yield	96.75
Corp. Bond General	164.17
Corp. Bond High Quality	131.25
Govt. Bond General	168.89
Govt. Bond Mortgage	173.99
Govt. Bond Treasury	217.70
Multi-Sector Bond	132.27
Long Govt.	283.82
Intermediate Govt.	173.66
Short Govt.	164.99
Long Bond	131.59
Intermediate Bond	176.99
Short Bond	134.74
Ultra-Short Bond	143.21
Bond Index Funds and ETF	92.00
Vanguard Tot. Bond Index	57.22
Equity Mutual Funds	85.80
Vanguard 500 Index Fund	5.00

Table III

Statistics of Asset Class Weights: Sector Allocation (1997-2006)

This table reports the mean, standard deviation, and range of the asset allocation weights for the sector allocations. End of year observations from 1997 to 2006 were used. Each statistic is calculated for each fund and then averaged across funds.

	Government	Credit	Mortgage	Foreign Bonds	Cash
All funds					
Mean	21.41	40.98	24.39	3.41	9.82
Std. Dev.	8.52	9.44	7.80	2.38	7.49
Range	25.07	27.11	22.53	6.88	21.59
Corp. Bond High Yield					
Mean	0.56	86.84	0.36	6.85	5.38
Std. Dev.	0.77	5.48	0.44	3.25	3.93
Range	2.23	16.28	1.30	9.47	11.50
Corp. Bond General					
Mean	18.56	45.63	21.57	2.92	11.32
Std. Dev.	8.68	11.53	8.63	2.39	8.26
Range	25.39	33.30	24.29	6.92	23.61
Corp. Bond High Quality					
Mean	20.41	44.03	22.29	2.11	11.16
Std. Dev.	9.52	12.24	9.24	2.15	7.77
Range	28.36	36.12	27.10	6.22	22.73
Govt. Bond General					
Mean	42.63	10.52	36.18	0.75	9.91
Std. Dev.	14.35	8.42	11.34	1.62	8.73
Range	42.81	23.10	33.66	4.89	25.02
Govt. Bond Mortgage					
Mean	9.32	4.76	76.75	0.18	8.99
Std. Dev.	6.96	4.25	10.20	0.43	7.54
Range	20.60	12.47	31.15	1.26	22.38
Govt. Bond Treasury					
Mean	76.73	8.24	6.93	0.37	7.73
Std. Dev.	16.37	8.03	4.74	0.77	9.01
Range	46.43	20.96	13.01	2.25	25.92
Multi-Sector Bond					
Mean	15.16	44.54	16.88	12.03	11.39
Std. Dev.	6.26	11.44	7.40	5.60	7.27
Range	17.83	32.14	20.00	15.61	20.32

Table IV

Statistics of Asset Class Weights: Credit Quality Allocation (1997-2006)

This table reports the mean, standard deviation, and range of the asset allocation weights for the credit quality allocation. I aggregated Govt/Agency weight with the AAA weight. End of year observations from 1997 to 2006 were used. Each statistic is calculated for each fund and then averaged across funds.

	Govt/ Agency/ AAA	AA	A	BBB	BB	B	B-
All funds							
Mean	59.85	4.03	9.21	8.61	5.99	10.50	1.80
Std. Dev.	7.15	2.52	3.90	3.97	2.57	2.87	1.34
Range	19.95	7.12	11.08	11.21	7.10	7.97	3.65
Corp. Bond High Yield							
Mean	3.06	0.29	0.90	4.74	24.59	56.80	9.61
Std. Dev.	3.35	0.47	1.24	4.18	8.12	11.57	6.07
Range	8.89	1.23	3.51	11.68	22.74	32.44	16.69
Corp. Bond General							
Mean	55.83	6.55	16.44	15.86	3.35	1.71	0.26
Std. Dev.	10.46	3.75	6.23	5.84	2.21	1.49	0.40
Range	29.42	10.38	17.66	16.42	6.10	4.03	1.09
Corp. Bond High Quality							
Mean	62.88	7.42	17.11	10.25	1.46	0.71	0.16
Std. Dev.	10.04	4.09	6.73	5.34	1.27	0.69	0.34
Range	28.30	11.81	19.29	15.34	3.50	1.92	0.99
Govt. Bond General							
Mean	95.61	1.31	1.89	0.99	0.09	0.07	0.03
Std. Dev.	3.32	1.39	1.47	0.99	0.16	0.16	0.09
Range	9.45	3.99	4.28	2.74	0.44	0.51	0.25
Govt. Bond Mortgage							
Mean	97.90	0.85	0.59	0.55	0.06	0.03	0.01
Std. Dev.	1.81	1.10	0.54	0.42	0.06	0.06	0.02
Range	5.40	3.34	1.67	1.35	0.18	0.19	0.05
Govt. Bond Treasury							
Mean	98.64	0.36	0.61	0.37	0.03	0.00	0.00
Std. Dev.	1.92	0.45	0.81	0.74	0.08	0.00	0.00
Range	5.04	1.16	2.11	2.12	0.24	0.00	0.00
Multi-Sector Bond							
Mean	47.50	4.57	7.02	11.07	11.92	15.03	2.89
Std. Dev.	11.14	3.00	3.50	4.42	5.03	6.40	2.80
Range	29.64	8.79	9.22	12.38	13.23	17.58	7.31

Table V

Statistics of Asset Class Weights: Maturity Range Allocation (1997-2006)

This table reports the mean, standard deviation, and range of the asset allocation weights for the maturity range allocation. End of year observations from 1997 to 2006 were used. Each statistic is calculated for each fund and then averaged across funds.

	0-1 Year	1-3 Year	3-5 Year	5-7 Year	7-10 Year	10 + Year
All funds						
Mean	15.78	14.33	12.18	18.87	7.26	31.57
Std. Dev.	7.52	6.88	5.56	7.39	4.72	9.68
Range	21.41	20.06	16.14	21.33	13.63	27.60
Corp. Bond High Yield						
Mean	4.83	13.27	27.32	46.36	3.47	4.76
Std. Dev.	3.17	5.37	7.26	11.57	2.30	3.06
Range	9.13	15.60	21.23	32.40	6.69	8.40
Corp. Bond General						
Mean	16.93	16.35	11.00	15.39	7.16	33.17
Std. Dev.	7.71	7.25	5.34	6.55	4.20	10.24
Range	21.79	20.82	15.34	18.90	12.04	28.95
Corp. Bond High Quality						
Mean	23.56	16.62	9.18	12.37	7.53	30.73
Std. Dev.	9.10	6.90	5.02	5.49	4.68	10.24
Range	26.29	20.39	14.64	16.20	13.73	29.36
Govt. Bond General						
Mean	20.20	13.70	7.25	12.70	9.95	36.20
Std. Dev.	10.18	8.35	5.75	7.87	6.91	12.13
Range	28.94	24.62	17.17	23.25	20.15	35.07
Govt. Bond Mortgage						
Mean	5.46	4.51	2.64	4.88	9.60	72.90
Std. Dev.	5.93	4.91	3.18	4.01	6.81	13.27
Range	16.85	14.95	9.13	11.84	20.41	38.85
Govt. Bond Treasury						
Mean	24.85	13.83	10.36	12.69	7.32	30.95
Std. Dev.	9.28	9.25	7.99	9.55	8.00	10.83
Range	26.45	27.34	22.18	27.76	20.48	29.08
Multi-Sector Bond						
Mean	11.60	14.05	14.70	23.43	6.44	29.78
Std. Dev.	6.70	5.59	4.83	7.86	3.31	9.90
Range	19.07	15.86	13.94	22.42	9.44	28.24

Table VI

Portfolio Allocation Turnover of Bond Funds and Selected Index Funds for Different Allocations

This table reports Portfolio Allocation Turnover as defined in equation (7). End of year observations from 1997 to 2006 were used. For the credit quality portfolio allocation turnover I aggregated Govt/Agency weights with the AAA weights.

	Sector Allocation	Credit Quality	Maturity Range
All Funds	14.20	9.21	16.81
Corp. Bond High Yield	6.08	13.09	12.50
Corp. Bond General	15.96	11.80	17.15
Corp. Bond High Quality	15.83	10.83	17.03
Govt. Bond General	17.13	2.73	20.91
Govt. Bond Mortgage	12.56	1.30	14.18
Govt. Bond Treasury	13.25	0.92	18.68
Multi-Sector Bond	15.48	13.48	16.07
Vanguard Total Bond Index	6.05	4.31	5.28
Vanguard Short-term Bond Index	7.73	6.77	4.88
Vanguard Intermediate Bond Index	6.29	10.07	11.71

Table VII

Morningstar Category and Style Changes

This table reports the number of bond funds that change Morningstar category and style and the frequency of the change. The sample consists of 969 bond funds described in Table 1. Morningstar places funds in a given category based on their portfolio statistics and compositions over the past three years. Morningstar bond style is a nine-square grid that classifies funds according to the duration and credit quality of their portfolio.

	Changes in Morningstar Category		Changes in Morningstar Style	
	# of Funds	# of changes	# of Funds	# of changes
All Funds	381	1018	735	3626
Corp. Bond High Yield	14	32	96	349
Corp. Bond General	134	354	255	1280
Corp. Bond High Quality	55	134	125	578
Govt. Bond General	97	309	122	598
Govt. Bond Mortgage	38	94	65	421
Govt. Bond Treasury	11	22	18	90
Multi-Sector Bond	32	73	54	310

Table VIII

Characteristic Timing (CT) Measure of Bond Funds Using Different Allocations and Horizons

This table presents the cross-sectional distribution of the weights-based Characteristic Timing (CT) measure and the P-values (in parentheses) which are obtained using bootstrapping as explained in the text. A low p-value (close to 0) implies that the estimated timing measure is consistently higher than its bootstrapped values and thus provides evidence of positive timing ability. By contrast, a high p-value (close to 1) implies that the estimated timing measure is consistently lower than its bootstrapped values and thus shows evidence of negative timing ability. The lag weight is the most recent weight up to 12 months. The figures are annualized and in %. In Panel A monthly returns data are used whereas in panel B daily returns data are used. Panel B presents a decomposition of the CT measure into a weighted average of the CT measure conditional on the days with macroeconomic announcements and in the CT measure conditional on the days with no announcements

Panel A: Using Monthly Returns Data

Allocation:	# of Funds	5%	10%	25%	Mean	Median	75%	90%	95%
Sector	751								
1-Month horizon		-0.496	-0.363	-0.175	-0.038	-0.017	0.109	0.261	0.386
		(0.552)	(0.668)	(0.730)	(0.732)	(0.603)	(0.663)	(0.723)	(0.759)
3-Month horizon		-0.386	-0.286	-0.143	-0.052	-0.044	0.048	0.167	0.248
		(0.740)	(0.799)	(0.792)	(0.883)	(0.903)	(0.931)	(0.814)	(0.818)
Credit Quality	634								
1-Month horizon		-0.501	-0.316	-0.109	0.076	0.049	0.252	0.492	0.650
		(0.050)	(0.058)	(0.083)	(0.176)	(0.204)	(0.294)	(0.484)	(0.697)
3-Month horizon		-0.370	-0.249	-0.115	0.028	0.001	0.141	0.295	0.470
		(0.238)	(0.297)	(0.477)	(0.329)	(0.567)	(0.438)	(0.506)	(0.375)
Maturity Range	932								
1-Month horizon		-0.454	-0.287	-0.101	0.040	0.014	0.161	0.365	0.576
		(0.413)	(0.350)	(0.158)	(0.023)	(0.109)	(0.038)	(0.082)	(0.066)
3-Month horizon		-0.271	-0.180	-0.076	0.008	0.001	0.085	0.206	0.294
		(0.086)	(0.102)	(0.198)	(0.267)	(0.391)	(0.489)	(0.615)	(0.771)

Panel B: Using Daily Returns Data (1-Month Horizon)

Allocations:	5%	10%	25%	Mean	Median	75%	90%	95%
Sector								
Announcement days	-0.539	-0.389	-0.174	-0.019	-0.005	0.143	0.348	0.494
Non-announcement days	-0.366	-0.259	-0.139	-0.045	-0.033	0.055	0.154	0.258
All trading days	-0.694	-0.518	-0.242	-0.064	-0.042	0.135	0.348	0.525
Credit Quality								
Announcement days	-0.583	-0.400	-0.146	0.071	0.067	0.237	0.558	0.716
Non-announcement days	-0.312	-0.185	-0.070	0.051	0.036	0.170	0.320	0.463
All trading days	-0.677	-0.429	-0.149	0.121	0.090	0.353	0.720	0.998
Maturity Range								
Announcement days	-0.528	-0.330	-0.136	0.046	0.007	0.183	0.440	0.688
Non-announcement days	-0.357	-0.226	-0.096	0.008	0.004	0.097	0.263	0.395
All trading days	-0.623	-0.393	-0.148	0.055	0.015	0.222	0.510	0.797

Table IX

Characteristic Timing (CT) Measure of Bond Funds by Style Group Using Credit Quality and Maturity Range Allocations

This table presents the cross-sectional distribution of the weights-based Characteristic Timing (CT) measure and the P-values (in parentheses) which are obtained using bootstrapping as explained in the text. A low p-value (close to 0) implies that the estimated timing measure is consistently higher than its bootstrapped values and thus provides evidence of positive timing ability. By contrast, a high p-value (close to 1) implies that the estimated timing measure is consistently lower than its bootstrapped values and thus shows evidence of negative timing ability. The lag weight is the most recent weight up to 12 months. The figures are annualized and in %. Panel A presents the results using the credit quality allocation and panel B presents the results using the maturity range allocation.

Panel A: Using the Credit Quality Allocation

	# of Funds	5%	10%	25%	Mean	Median	75%	90%	95%
Corp. High Yield	107								
1-Month horizon		-0.750	-0.628	-0.185	0.088	0.111	0.402	0.766	1.050
		(0.077)	(0.311)	(0.109)	(0.174)	(0.052)	(0.140)	(0.420)	(0.626)
3-Month horizon		-0.856	-0.432	-0.150	0.081	0.052	0.237	0.685	1.164
		(0.792)	(0.414)	(0.263)	(0.091)	(0.118)	(0.205)	(0.043)	(0.024)
Corp. Bond General	235								
1-Month horizon		-0.413	-0.282	-0.114	0.018	0.004	0.164	0.363	0.494
		(0.156)	(0.173)	(0.196)	(0.426)	(0.526)	(0.587)	(0.558)	(0.636)
3-Month horizon		-0.338	-0.230	-0.105	-0.012	-0.013	0.078	0.216	0.301
		(0.638)	(0.575)	(0.554)	(0.663)	(0.717)	(0.834)	(0.591)	(0.596)
Corp. High Quality	125								
1-Month horizon		-0.507	-0.311	-0.137	0.023	0.014	0.143	0.269	0.448
		(0.590)	(0.418)	(0.467)	(0.381)	(0.439)	(0.596)	(0.820)	(0.658)
3-Month horizon		-0.379	-0.220	-0.098	-0.025	-0.016	0.072	0.168	0.206
		(0.873)	(0.652)	(0.614)	(0.806)	(0.773)	(0.799)	(0.832)	(0.953)
Multi-Sector Bond	46								
1-Month horizon		-0.680	-0.254	-0.065	0.160	0.155	0.340	0.550	0.934
		(0.132)	(0.009)	(0.027)	(0.102)	(0.034)	(0.333)	(0.713)	(0.617)
3-Month horizon		-0.513	-0.263	-0.102	0.158	0.074	0.215	0.676	1.454
		(0.261)	(0.096)	(0.180)	(0.023)	(0.101)	(0.359)	(0.063)	(0.011)

Panel B: Using the Maturity Range Allocation

	# of Funds	5%	10%	25%	Mean	Median	75%	90%	95%
Corp. High Yield	148								
1-Month horizon		-0.224	-0.137	-0.078	0.003	-0.020	0.036	0.114	0.211
		(0.827)	(0.673)	(0.839)	(0.339)	(0.807)	(0.691)	(0.444)	(0.171)
3-Month horizon		-0.133	-0.107	-0.049	-0.025	-0.008	0.019	0.059	0.118
		(0.583)	(0.803)	(0.639)	(0.872)	(0.581)	(0.808)	(0.841)	(0.475)
Corp. Bond General	311								
1-Month horizon		-0.487	-0.324	-0.124	0.019	0.017	0.185	0.357	0.494
		(0.580)	(0.543)	(0.358)	(0.192)	(0.157)	(0.047)	(0.190)	(0.323)
3-Month horizon		-0.280	-0.209	-0.100	0.001	-0.009	0.088	0.205	0.317
		(0.138)	(0.297)	(0.503)	(0.392)	(0.653)	(0.587)	(0.643)	(0.518)

Table IX - *Continued*

	# of Funds	5%	10%	25%	Mean	Median	75%	90%	95%
Corp. High Quality	145								
1-Month horizon		-0.290	-0.208	-0.083	0.045	0.034	0.151	0.311	0.495
		(0.052)	(0.086)	(0.089)	(0.065)	(0.087)	(0.247)	(0.361)	(0.204)
3-Month horizon		-0.209	-0.154	-0.067	0.021	0.015	0.103	0.206	0.279
		(0.065)	(0.096)	(0.160)	(0.238)	(0.274)	(0.421)	(0.618)	(0.739)
Govt. Bond General	158								
1-Month horizon		-0.580	-0.439	-0.165	0.062	0.042	0.211	0.594	0.771
		(0.358)	(0.615)	(0.481)	(0.068)	(0.055)	(0.166)	(0.031)	(0.147)
3-Month horizon		-0.368	-0.253	-0.123	-0.024	-0.004	0.089	0.234	0.303
		(0.264)	(0.318)	(0.574)	(0.811)	(0.638)	(0.931)	(0.853)	(0.937)
Govt. Bond Mortgage	71								
1-Month horizon		-0.723	-0.452	-0.070	0.053	0.048	0.241	0.554	0.883
		(0.767)	(0.743)	(0.034)	(0.165)	(0.035)	(0.057)	(0.105)	(0.123)
3-Month horizon		-0.306	-0.236	-0.056	0.022	0.025	0.137	0.257	0.364
		(0.148)	(0.296)	(0.085)	(0.321)	(0.091)	(0.226)	(0.652)	(0.752)
Govt. Bond Treasury	31								
1-Month horizon		-0.377	-0.353	-0.112	0.020	0.031	0.159	0.431	0.776
		(0.067)	(0.263)	(0.112)	(0.272)	(0.170)	(0.487)	(0.388)	(0.187)
3-Month horizon		-0.276	-0.223	-0.061	0.054	0.088	0.183	0.332	0.416
		(0.102)	(0.185)	(0.054)	(0.045)	(0.002)	(0.060)	(0.207)	(0.346)
Multi-Sector Bond	68								
1-Month horizon		-0.494	-0.260	-0.082	0.143	0.021	0.169	0.391	0.645
		(0.589)	(0.331)	(0.156)	(0.008)	(0.220)	(0.156)	(0.119)	(0.126)
3-Month horizon		-0.188	-0.141	-0.050	0.115	0.045	0.132	0.206	0.383
		(0.040)	(0.075)	(0.054)	(0.006)	(0.033)	(0.099)	(0.474)	(0.252)

Table X

Mutual Fund Return Decomposition: Average Style, Characteristic Timing, and Return GAP

This table presents the return decomposition of mutual fund returns plus expenses and transaction costs in the Characteristic Timing measure, Average Style and Return GAP for an equally-weighted and value-weighted portfolio of funds. I used the asset class allocation adjusted for credit quality and maturity exposure as in equation (8). The mean is annualized and in %. The T-statistics (tests on the null that the mean is equal to zero) are computed using Newey-West consistent standard errors.

		Net Return	Expense Ratio	Trans. Costs	Average Style	Characteristic Timing		Return GAP		RG post expenses & costs	
	# of Funds	Mean	Mean	Mean	Mean	Mean	T-stat	Mean	T-stat	Mean	T-stat
Equally-weighted portfolio of funds											
All funds	683	5.317	0.818	0.524	5.556	0.019	0.108	1.093	3.954	-0.250	-0.905
Corp. High Yield	100	5.051	1.057	0.745	4.926	-0.057	-0.248	1.993	2.173	0.191	0.210
Corp. Bond General	220	5.513	0.759	0.760	5.481	-0.009	-0.048	1.559	4.018	0.038	0.098
Corp. High Quality	104	5.086	0.673	0.622	5.245	0.101	0.539	1.042	3.283	-0.252	-0.790
Govt. Bond General	127	5.017	0.841	0.197	5.643	0.054	0.244	0.379	1.230	-0.660	-2.137
Govt. Bond Mortgage	62	5.057	0.779	0.323	6.569	0.024	0.074	-0.434	-0.443	-1.538	-1.569
Govt. Bond Treasury	26	5.943	0.595	0.154	5.193	0.133	0.769	1.356	1.676	0.609	0.752
Multi-Sector Bond	44	5.625	1.148	0.411	5.371	0.049	0.219	1.785	2.936	0.224	0.370
Value-weighted portfolio of funds											
All funds	683	5.269	0.832	0.562	5.681	0.015	0.074	1.000	3.997	-0.392	-1.528
Corp. High Yield	100	5.069	1.044	0.694	4.843	0.009	0.035	1.942	1.973	0.208	0.212
Corp. Bond General	220	5.542	0.765	0.715	5.573	0.003	0.013	1.447	4.244	-0.034	-0.097
Corp. High Quality	104	4.885	0.663	0.737	5.054	0.068	0.356	1.168	2.862	-0.231	-0.562
Govt. Bond General	127	5.084	0.877	0.234	6.118	-0.036	-0.116	0.231	0.699	-0.871	-2.643
Govt. Bond Mortgage	62	5.385	0.731	0.241	6.709	-0.016	-0.052	-0.334	-0.317	-1.309	-1.240
Govt. Bond Treasury	26	5.114	0.596	0.241	4.772	0.161	0.900	0.949	1.493	0.109	0.172
Multi-Sector Bond	44	4.737	1.120	0.689	5.261	-0.108	-0.541	1.424	3.234	-0.395	-0.915

Table XI

Regression of return GAP on Monthly Dummies

This table shows the percentage of funds with a given fiscal year-end and the results of regression of the return GAP (with equally weighted portfolio of funds) on an intercept and monthly dummies. It also reports the p-values of an F-test on the dummy variables.

	Fiscal Year-End: % of Funds	Regression Estimate	T-stat	Regression Estimate	T-stat	Regression Estimate	T-stat
Intercept		0.07	2.03	0.12	3.45	0.09	2.91
January	3.21			-0.02	-0.22	0.01	0.13
February	2.83						
March	9.38	-0.02	-0.24				
April	2.96	0.02	0.28	-0.02	-0.26	0.01	0.08
May	6.43			-0.15	-1.65		
June	5.14	0.08	0.93				
July	5.27			0.08	0.85	0.11	1.20
August	6.68						
September	15.04	0.15	1.68				
October	17.22	-0.03	-0.27	-0.07	-0.79	-0.04	-0.46
November	4.11			-0.10	-1.08		
December	21.72	0.08	0.88				
F-test (p-value)		0.62		0.51		0.77	

Table XII

Estimates of the Unconditional and Conditional Index Model

This table reports the results from time-series regressions of bond mutual fund excess returns on the excess return of selected indices (Panel A) and on the excess return of selected indices and their product with a vector of predetermined instruments (Panel B). The instruments include the following variables lagged one period: term spread (the difference between the 10-year and 3-month Treasury yield), the 3-month Treasury rate, commercial paper spread (the yield difference between three-month nonfinancial corporate commercial paper rates and the three month Treasury yield), default spread (the difference between the yield on BAA corporate bonds and AAA corporate bonds), US dollar exchange rate relative to a trade-weighted average of major trading partners, the VIX index, the aggregate dividend yield for stocks in the S&P500. To conserve space the estimates for the interaction terms are not shown. An equally-weighted portfolio of funds is used. For Treasury funds the indices are three Treasury indices with short, medium, and long maturities. The t-statistics (in parentheses) are calculated using heteroskedasticity-consistent standard errors. The sample period is from January 1997 to September 2006. The alphas were annualized by multiplying by 12. The F-test (p-values) column reports p-values of the exclusion test for the additional terms in the conditional model.

Panel A: Unconditional Index Model

	Alpha	Treasury	Mortgage	Corporate	High-Yield	Foreign	S&P500	Adj. R^2
All funds	-0.483	0.237	0.269	0.168	0.150	0.019	0.007	0.988
	(-4.587)	(11.279)	(13.691)	(8.052)	(17.524)	(0.908)	(3.424)	
Corp. Bond High Yield	-1.161			-0.101	0.867	0.164	0.044	0.946
	(-2.115)			(-2.879)	(16.970)	(1.639)	(2.893)	
Corp. Bond General	-0.387	0.170	0.248	0.392	0.042			0.986
	(-3.059)	(5.650)	(8.670)	(12.051)	(6.405)			
Corp. Bond High Quality	-0.310	0.227	0.210	0.231	0.014			0.977
	(-2.445)	(6.596)	(7.733)	(6.940)	(1.947)			
Govt. Bond General	-0.544	0.477	0.317	0.019				0.988
	(-5.159)	(24.995)	(12.086)	(1.006)				
Govt. Bond Mortgage	-0.453	0.115	0.660					0.982
	(-4.317)	(9.144)	(30.577)					
Multi-Sector Bond	-0.938	-0.067	0.284	0.340	0.265	0.305	0.067	0.868
	(-1.707)	(-0.352)	(2.796)	(2.105)	(7.159)	(3.498)	(4.964)	
		TRSY 1-3	TRSY 5-7	TRSY10+				
Govt. Bond Treasury	-0.242	-0.426	0.380	0.618				0.955
	(-0.690)	(-1.831)	(2.169)	(7.298)				

Table XII - *Continued*

Panel B: Conditional Index Model

	Alpha	Treasury	Mortgage	Corporate	High-Yield	Foreign	S&P500	Adj. R^2	F-test (p-values)
All funds	-0.548	0.264	0.240	0.152	0.175	0.029	0.009	0.991	0.004
	(-5.659)	(7.617)	(9.434)	(4.598)	(18.349)	(1.685)	(3.304)		
Corp. Bond High Yield	-0.835			-0.128	0.966	0.088	0.041	0.981	0.000
	(-2.439)			(-4.091)	(39.236)	(1.659)	(4.756)		
Corp. Bond General	-0.462	0.212	0.213	0.361	0.066			0.991	0.000
	(-3.990)	(6.076)	(7.901)	(10.626)	(7.360)				
Corp. Bond High Quality	-0.362	0.311	0.176	0.170	0.032			0.984	0.000
	(-3.069)	(6.926)	(5.949)	(3.960)	(3.452)				
Govt. Bond General	-0.580	0.483	0.317	0.012				0.993	0.000
	(-6.400)	(24.621)	(14.098)	(0.665)					
Govt. Bond Mortgage	-0.500	0.134	0.651					0.984	0.018
	(-4.575)	(9.078)	(20.860)						
Multi-Sector Bond	-0.936	-0.483	0.300	0.700	0.317	0.144	0.053	0.922	0.000
	(-1.944)	(-3.698)	(2.673)	(5.554)	(7.005)	(1.942)	(4.348)		
		TRSY 1-3	TRSY 5-7	TRSY10+					
Govt. Bond Treasury	-0.417	-0.160	-0.233	1.109				0.979	0.000
	(-1.511)	(-1.117)	(-1.911)	(15.437)					

Table XIII

Conditional and Unconditional Characteristic Timing Measures for Different Portfolio Allocations

This table presents the cross-sectional distribution of the weights-based Characteristic Timing measure and Conditional Characteristic Timing measure as defined in equations (2) and (6) with 1-Month horizon. The lag weight is the most recent weight up to 12 months. The difference between the two measures is also presented. Monthly returns data were used. The figures are annualized and in %. The P-values (in parentheses) are obtained using bootstrapping as explained in the text. A low p-value (close to 0) implies that the estimated timing measure is consistently higher than its bootstrapped values and thus provides evidence of positive timing ability. By contrast, a high p-value (close to 1) implies that the estimated timing measure is consistently lower than its bootstrapped values and thus shows evidence of negative timing ability.

	5%	10%	25%	Mean	Median	75%	90%	95%
Sector								
CT conditional	-0.418	-0.267	-0.130	0.001	-0.002	0.141	0.294	0.421
	(0.441)	(0.337)	(0.521)	(0.489)	(0.522)	(0.391)	(0.517)	(0.560)
CT unconditional	-0.462	-0.352	-0.164	-0.026	-0.009	0.118	0.277	0.402
	(0.498)	(0.691)	(0.728)	(0.735)	(0.622)	(0.677)	(0.705)	(0.743)
Difference	-0.044	-0.085	-0.034	-0.026	-0.007	-0.023	-0.016	-0.020
Credit Quality								
CT conditional	-0.645	-0.407	-0.140	0.055	0.023	0.251	0.534	0.863
	(0.121)	(0.140)	(0.133)	(0.246)	(0.308)	(0.286)	(0.460)	(0.442)
CT unconditional	-0.594	-0.396	-0.129	0.096	0.051	0.273	0.606	0.920
	(0.019)	(0.063)	(0.066)	(0.128)	(0.148)	(0.291)	(0.400)	(0.496)
Difference	0.050	0.011	0.011	0.041	0.029	0.022	0.072	0.057
Maturity Range								
CT conditional	-0.413	-0.258	-0.097	0.031	0.011	0.143	0.323	0.548
	(0.387)	(0.278)	(0.234)	(0.041)	(0.182)	(0.055)	(0.104)	(0.021)
CT unconditional	-0.453	-0.296	-0.096	0.043	0.016	0.171	0.369	0.560
	(0.427)	(0.469)	(0.133)	(0.018)	(0.121)	(0.026)	(0.063)	(0.084)
Difference	-0.040	-0.038	0.001	0.012	0.004	0.028	0.046	0.012

Table XIV

Weight Change Test of Market Timing Ability for Different Portfolio Allocations

This table reports the average bond index excess returns (in excess of the risk-free rate) for different asset classes during the month following the largest weight increase and decrease in each reporting period. A fund is included if it has at least 5 observations of both weight increases and weight decreases in any of the asset classes. The T-statistics are obtained with a t-test on the mean difference.

	GOVT	Credit	Mortgage	Foreign	Cash			
Weight increased	-0.77	0.13	1.39	3.09	-0.11			
Weight decreased	0.67	1.84	2.41	0.06	-0.13			
Tstat mean difference	-3.82	-4.34	-3.24	4.19	1.35			
# of funds	253	274	167	34	386			
	0-1 Year	1-3 Year	3-5 Year	5-7 Year	7-10 Year	10-30 Year		
Weight increased	0.070	0.876	1.926	1.868	1.846	3.589		
Weight decreased	0.006	0.817	1.438	2.505	2.587	1.673		
Tstat mean difference	4.537	0.522	1.685	-1.961	-1.026	3.252		
# of funds	383	483	312	423	186	494		
	GOVT/Agency	AAA	AA	A	BBB	BB	B	B-
Weight increased	0.345	2.662	6.029	2.413	2.510	5.088	7.369	8.394
Weight decreased	2.561	0.388	1.416	4.830	1.946	7.351	4.159	8.045
Tstat mean difference	-5.942	5.625	1.581	-1.512	0.424	-2.057	2.671	0.117
# of funds	362	372	8	39	49	60	81	26

Table XV

Persistence of Characteristic Timing and Return Gap

This table reports the average Characteristic Timing and Return Gap during the subsequent month (panel A), quarter (panel B), and year (panel C) after sorting the funds in quintiles. The funds are sorted according to the average CT and return GAP during the previous year and previous two years. The funds in each quintile are weighted equally. The measures are calculated using a 12-month horizon.

Panel A: 1-Month Holding period								
Length Past Window:	1 Year				2 Year			
	CT	T-stat	GAP	T-stat	CT	T-stat	GAP	T-stat
1 Quintile (lowest)	-0.070	-0.240	0.340	0.412	-0.258	-0.810	0.507	0.586
2 Quintile	-0.086	-0.322	0.820	2.510	-0.090	-0.306	0.862	2.476
3 Quintile	-0.096	-0.354	0.930	2.991	-0.088	-0.286	0.942	2.874
4 Quintile	0.032	0.106	1.206	2.687	-0.075	-0.226	1.038	2.201
5 Quintile (highest)	0.290	0.773	1.998	2.716	0.268	0.741	2.001	2.648
5-1 Quintile	0.360	0.994	1.658	1.412	0.526	1.622	1.494	1.228
Panel B: 1-Quarter Holding period								
Length Past Window:	1 Year				2 Year			
	CT	T-stat	GAP	T-stat	CT	T-stat	GAP	T-stat
1 Quintile (lowest)	-0.213	-0.926	0.481	0.724	-0.331	-1.587	0.429	0.612
2 Quintile	-0.100	-0.697	0.919	3.067	-0.079	-0.430	0.959	2.549
3 Quintile	-0.103	-0.742	1.039	3.068	-0.104	-0.668	0.978	2.826
4 Quintile	0.050	0.257	1.123	2.629	-0.010	-0.053	1.039	2.589
5 Quintile (highest)	0.428	1.420	1.803	2.685	0.319	1.142	2.012	3.325
5-1 Quintile	0.641	3.023	1.322	1.915	0.650	2.344	1.583	1.700
Panel C: 1-Year Holding period								
Length Past Window:	1 Year				2 Year			
	CT	T-stat	GAP	T-stat	CT	T-stat	GAP	T-stat
1 Quintile (lowest)	-0.008	-0.039	0.829	1.162	-0.035	-0.198	0.663	0.986
2 Quintile	-0.009	-0.076	1.121	2.699	-0.030	-0.251	1.008	2.135
3 Quintile	0.024	0.166	0.930	2.575	-0.093	-0.661	1.048	2.418
4 Quintile	-0.066	-0.518	1.104	2.595	-0.046	-0.261	0.837	1.596
5 Quintile (highest)	0.192	0.791	1.381	1.850	0.040	0.188	1.885	2.141
5-1 Quintile	0.201	1.597	0.552	0.386	0.075	0.537	1.222	0.743

Table XVI

Return Gap Measure and Mutual Fund Characteristics

This table reports the coefficients and t-statistics of panel regressions of the Return Gap measures on various fund characteristics. The measures are calculated using 12-month horizon. The independent variables are standardized. The regression includes both fund-fixed effects and time-fixed effects (Panel A) and only time-fixed effects (Panel B). The t-statistics are obtained using robust standard errors clustering by funds.

Panel A: With Fund-fixed Effects and Time-fixed Effects

	GAP	T-stat	GAP post TC	T-stat	GAP post Exp. & TC	T-stat	GAP	T-stat	GAP	T-stat	GAP	T-stat
Log (TNA)	-0.128	-7.295	-0.120	-7.940	-0.121	-8.086	-0.115	-6.899	-0.128	-7.313	-0.097	-5.757
Log (TNA) * HYDummy											-0.179	-3.649
Cash	0.003	0.698	0.004	0.889	0.004	0.851	0.002	0.530	0.003	0.707	0.007	1.489
Duration	-0.007	-0.861	-0.009	-1.026	-0.008	-0.985	-0.017	-2.116	-0.007	-0.861	-0.009	-1.096
Credit Quality	0.019	1.199	0.019	1.209	0.020	1.325	0.014	0.849	0.019	1.202	0.028	1.764
Turnover	0.042	5.615	0.010	1.688	0.010	1.765	0.042	5.816	0.042	5.615	0.040	5.567
Flow (1-Month)	-0.001	-1.836	-0.001	-1.166	-0.001	-1.228	-0.001	-1.146			-0.002	-2.233
Flow (1-Quarter)									-0.037	-2.192		
Volatility Flow	-0.023	-2.944	-0.025	-3.395	-0.025	-3.470	-0.025	-3.069	-0.023	-2.890	-0.022	-2.805
Log (Age)	0.029	1.532	0.023	1.299	0.024	1.356	0.037	2.069	0.029	1.530	0.033	1.797
Distribution Yield	-0.073	-2.699	-0.073	-2.702	-0.072	-2.689	-0.062	-2.367	-0.073	-2.693	-0.029	-1.360
Distribution Yield * HYDummy											-0.093	-2.812
Expense Ratio	-0.003	-0.251	-0.002	-0.138	-0.020	-1.608	-0.014	-1.111	-0.003	-0.256	-0.005	-0.389
Morningstar Rating	0.081	11.353	0.082	11.548	0.083	11.650			0.081	11.355	0.077	9.819
Alpha							0.026	3.814				

Table XVI - *Continued*

Panel B: With Time-fixed Effects												
	GAP	T-stat	GAP post TC	T-stat	GAP post Exp. & TC	T-stat	GAP	T-stat	GAP	T-stat	GAP	T-stat
Log (TNA)	-0.020	-3.266	-0.018	-3.632	-0.019	-3.880	-0.015	-2.632	-0.020	-3.271	-0.018	-3.470
Log (TNA) * HYDummy											-0.016	-0.989
Cash	0.006	1.253	0.005	1.058	0.004	0.995	0.008	1.812	0.006	1.258	0.009	2.118
Duration	0.037	9.041	0.037	9.335	0.037	9.235	0.035	8.386	0.037	9.040	0.033	8.420
Credit Quality	-0.090	-7.492	-0.071	-6.106	-0.071	-6.153	-0.073	-7.084	-0.090	-7.488	-0.101	-7.494
Turnover	0.049	6.328	0.003	0.850	0.003	0.930	0.053	6.637	0.049	6.329	0.050	6.716
Flow (1-Month)	-0.001	-2.559	-0.001	-2.247	-0.001	-2.411	-0.002	-2.853			-0.001	-2.681
Flow (1-Quarter)									-0.021	-1.052		
Volatility Flow	-0.006	-0.997	-0.008	-1.347	-0.006	-1.127	-0.001	-0.107	-0.006	-0.984	-0.004	-0.663
Log (Age)	-0.004	-0.629	-0.003	-0.485	-0.003	-0.590	-0.008	-1.438	-0.004	-0.632	-0.002	-0.378
Distribution Yield	-0.049	-2.337	-0.047	-2.257	-0.048	-2.306	-0.041	-2.240	-0.049	-2.333	-0.016	-1.148
Distribution Yield * HYDummy											-0.067	-2.584
Expense Ratio	0.016	3.066	0.021	4.139	-0.006	-1.286	-0.009	-1.787	0.016	3.071	0.015	2.926
Morningstar Rating	0.072	12.113	0.071	12.421	0.072	12.654			0.072	12.120	0.067	11.691
Alpha							0.044	6.077				
Nobs	51443		51443		51443		51425				51443	

Table XVII

Characteristic Timing Measure and Mutual Fund Characteristics

This table reports the coefficients and t-statistics of panel regressions of the Characteristic Timing measures on various fund characteristics. The measures are calculated using 12-month horizon. The independent variables are standardized. The regression includes both fund-fixed effects and time-fixed effects and only time-fixed. The t-statistics are obtained using robust standard errors clustering by funds.

	With both fund-fixed effects and time-fixed effects				With only time-fixed effects			
	CT	T-stat	CT	T-stat	CT	T-stat	CT	T-stat
Log (TNA)	0.014	2.522	0.014	2.459	0.005	2.299	0.004	1.871
Cash	-0.007	-3.192	-0.007	-2.749	-0.006	-3.393	-0.006	-3.231
Duration	-0.007	-1.681	-0.001	-0.398	-0.004	-2.822	-0.003	-2.208
Credit Quality	0.007	0.964	0.005	0.565	0.008	2.472	0.010	2.885
Turnover	0.000	0.103	-0.002	-0.729	0.000	0.209	0.000	0.098
Flow (1-Month)	0.000	-0.971	0.000	-2.340	0.000	1.500	0.000	1.472
Volatility Flow	0.006	1.622	0.005	1.543	0.002	1.652	0.002	1.386
Log (Age)	-0.010	-1.066	-0.009	-0.848	-0.002	-0.861	-0.001	-0.334
Distribution Yield	-0.003	-0.681	-0.002	-0.302	0.000	-0.015	0.002	0.442
Morningstar Rating	-0.005	-2.013			-0.005	-2.429		
Alpha			0.003	1.103			0.004	1.899
Expense Ratio	-0.003	-0.508	0.004	0.702	0.002	0.767	0.004	1.827
Nobs	51122				51122			

Table XVIII

Portfolio Returns Based on Past Alpha and Return GAP

This table reports the average returns and risk adjusted returns together with the t-statistics of quintile portfolios during the subsequent month after sorting the funds in quintiles. The funds are sorted according to the average alpha (Panel A) and return GAP (Panel B) during the previous year and previous two years. The alphas are the unconditional Jensen alphas of Section 6.3 calculated using a two-year window. The funds in each quintile are weighted equally. The risk-adjusted returns are obtained by estimating a Jensen alpha from an unconditional multi-index model using the excess returns on the Treasury, mortgage, corporate, high-yield, foreign, and equity index.

Panel A: Sorting Criterion Based on Past Alpha

Length Past Window:	1 Year				2 Year			
	Raw Returns	T-stat	Risk-Adj. Returns	T-stat	Raw Returns	T-stat	Risk-Adj. Returns	T-stat
1 Quintile (lowest)	4.387	3.334	-1.118	-3.316	4.277	3.271	-1.238	-4.042
2 Quintile	4.704	4.115	-0.548	-3.539	4.828	4.174	-0.450	-2.661
3 Quintile	4.705	4.546	-0.363	-2.757	4.701	4.365	-0.375	-3.159
4 Quintile	4.755	5.239	-0.115	-0.727	4.736	5.239	-0.129	-0.917
5 Quintile (highest)	5.271	4.757	0.205	0.634	5.283	4.991	0.264	1.004
5-1 Quintile	0.884	1.485	1.323	2.389	1.006	1.861	1.501	3.365

Panel B: Sorting Criterion Based on Past Return GAP

Length Past Window:	1 Year				2 Year			
	Raw Returns	T-stat	Risk-Adj. Returns	T-stat	Raw Returns	T-stat	Risk-Adj. Returns	T-stat
1 Quintile (lowest)	3.496	3.461	-1.518	-4.283	3.588	3.661	-1.493	-4.652
2 Quintile	4.548	4.465	-0.458	-3.242	4.721	4.698	-0.294	-2.122
3 Quintile	4.703	4.314	-0.401	-2.223	4.621	4.292	-0.471	-3.438
4 Quintile	5.262	4.800	0.072	0.336	5.116	4.582	-0.068	-0.359
5 Quintile (highest)	5.817	4.637	0.367	0.980	5.778	4.606	0.398	1.146
5-1 Quintile	2.321	3.477	1.885	2.903	2.190	3.523	1.890	3.292

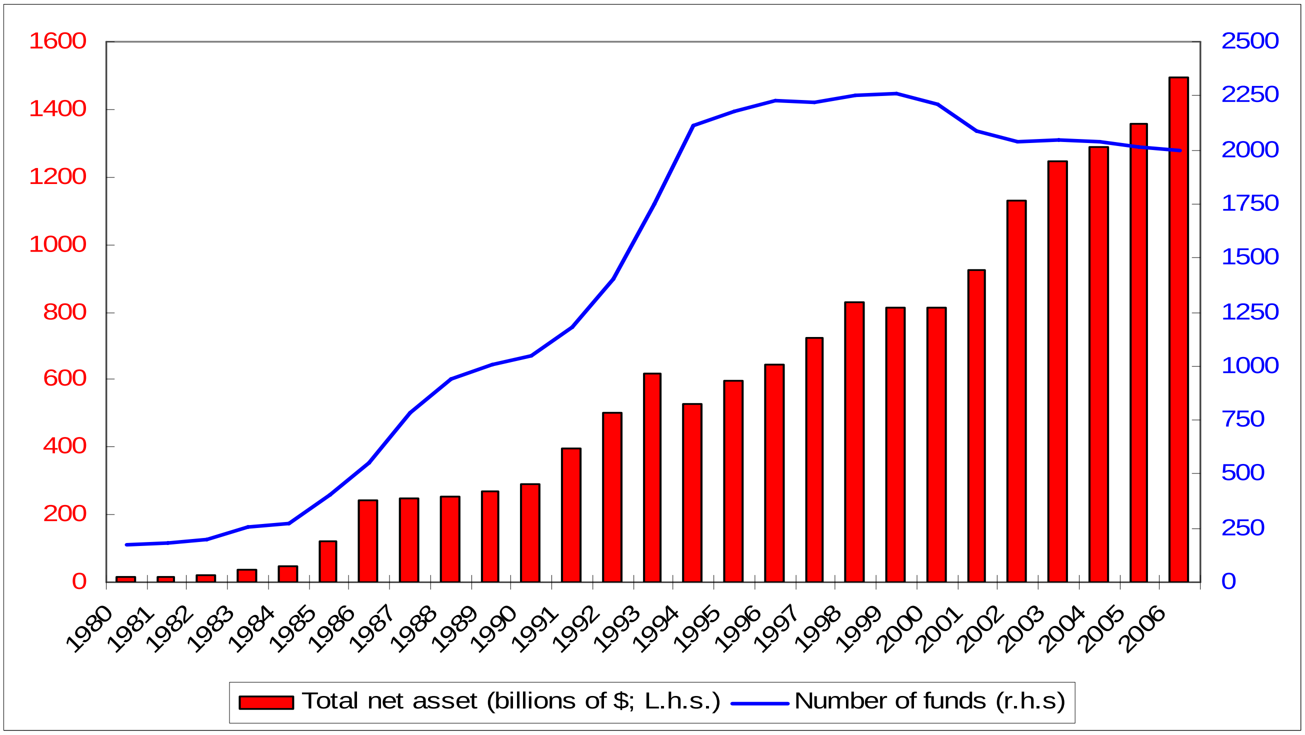

Figure 1: Recent Trends in Bond Mutual Funds. Source: Investment Company Institute; money market funds are not included.

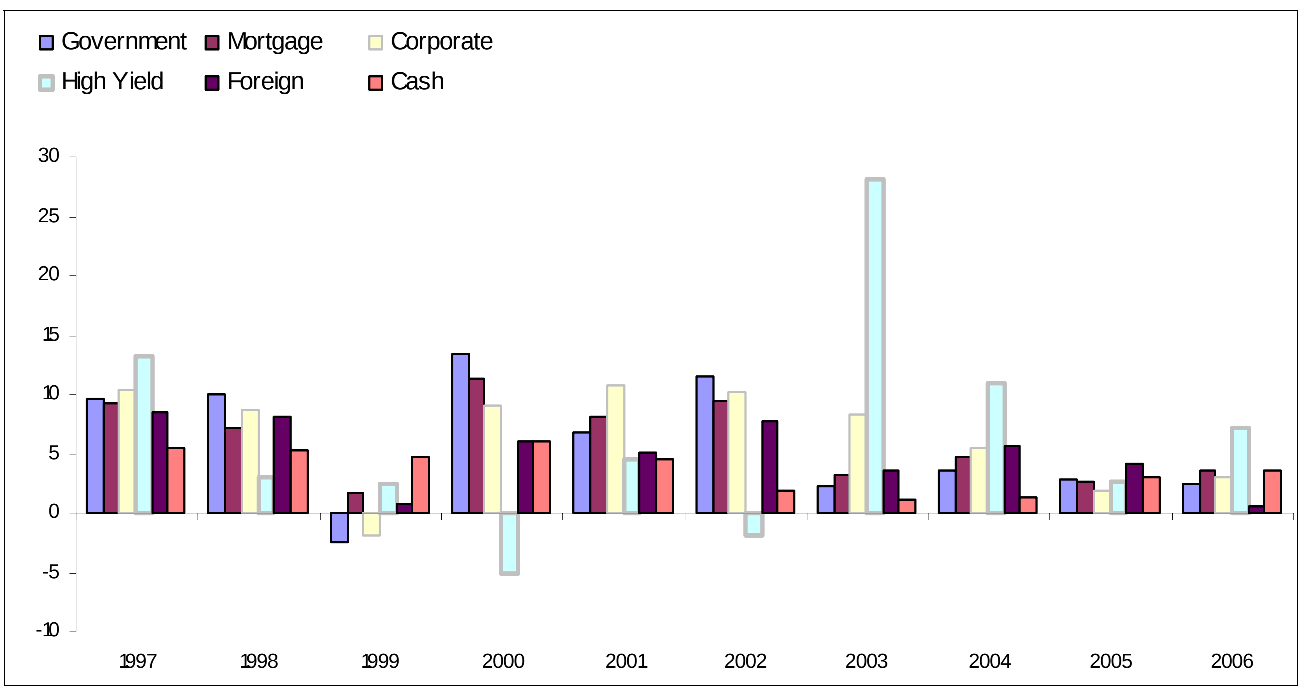

Figure 2: Annual Returns for Selected Fixed-income Indices (1997-2006). Source: Bloomberg. : The figures have been annualized by multiplying the monthly mean by 12 and the monthly standard deviation by the square root of 12.

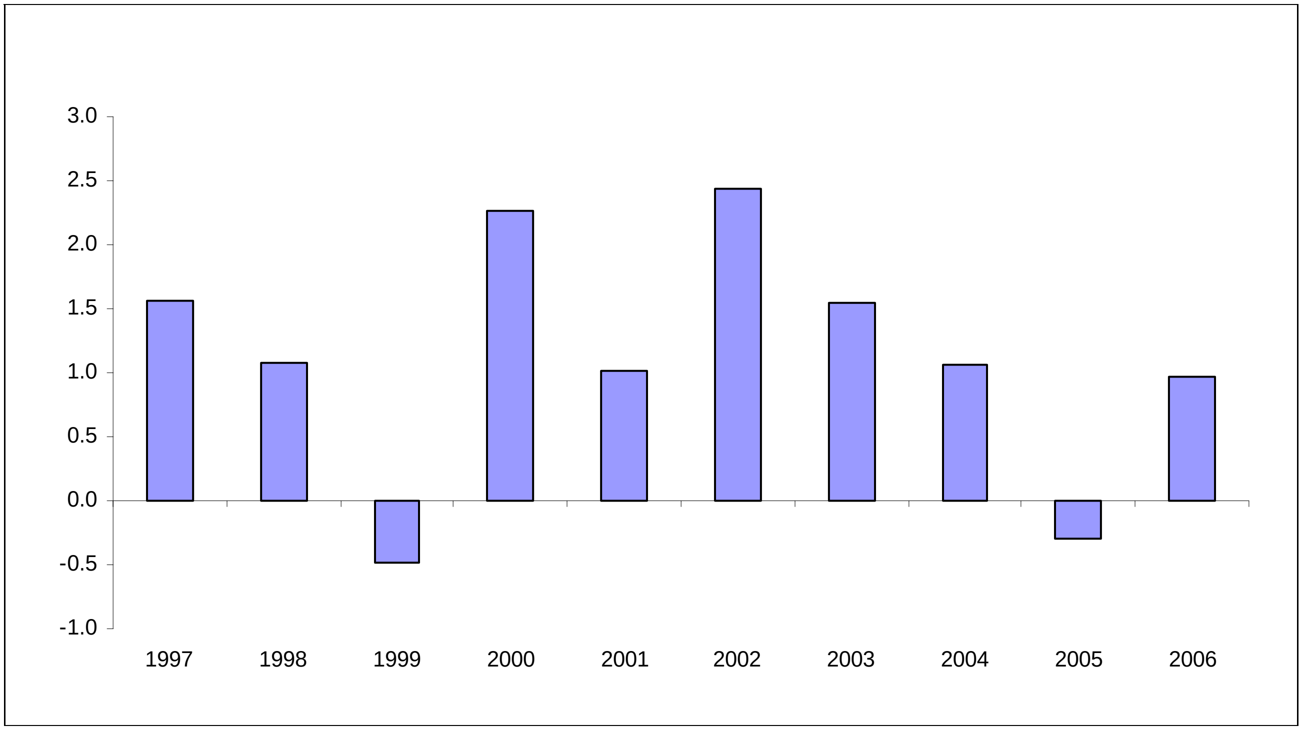

Figure 3: Annual Return GAP for an Equally-weighted Portfolio of 683 Bond Funds