Persistent Performance in Corporate-Bond Mutual Funds

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Abstract

We evaluate the performances of corporate-bond mutual funds from 1990 to 2004. On average, funds generate slightly positive abnormal returns before fees and slightly negative abnormal returns after fees. Moreover, the top decile of funds over the past year outperforms the bottom decile, net of expenses and trading costs, by ten basis points per month over the next four years for high-quality funds and twenty basis points per month for high-yield funds. This persistent performance seems due to the bond-selection skill of the winning managers. Remarkably, the winners are able to generate positive alpha gross of expenses over the next four years. Investors exploit this persistence in performance for high-yield funds, as funds with inflows outperform funds with outflows over the next year. Finally, since the returns of the underlying corporate bonds do not display momentum, it is noteworthy to find evidence of persistence and rewards to chasing past performance since these two findings for equity funds depend heavily on the confounding influence of momentum in the underlying stock returns.

1 Introduction

Is mutual-fund performance persistent, and if so, can investors take advantage of such persistence? Much of the financial economics literature has been focused on this topic; however, the evidence thus far relies almost exclusively on equity funds. We begin to fill this gap in knowledge by examining the performances of mutual funds investing primarily in corporate bonds, which like equities, derive their values from the cash flows of the firm.[1]

We are also motivated to examine corporate-bond funds in light of the current difficulty in interpreting evidence of persistence in the performance of equity funds. Hendricks, Patel, and Zeckhasuer (1993), Goetzmann and Ibbotson (1994), and Brown and Goetzmann (1995), among many others, find evidence of persistence in the relative performance of equity funds. Such persistence indicates that prior performance should be considered when selecting funds and suggests that some fund managers are better skilled than others. However, Carhart (1997) and Chen, Jegadeesh, and Wermers (2000) find that the persistence in the relative performance of equity funds is largely due to momentum in the underlying stock returns. This link between persistence in fund performance and stock-return momentum hinders concluding that fund performance truly persists.

The reason for this impasse is that it is unclear how to view momentum in stock returns. Is momentum a measure of risk or just a predictor of future abnormal performance? The first view requires that we adjust performance for momentum; the second view does not. Additionally, our inability to determine if fund managers are passively or actively relying on momentum strategies to produce better performance further confuses our interpretation of the evidence on persistence. Performance evaluation should not reward passive investing. Carhart (1997) suggests that the better funds are mostly benefiting from passive investing in momentum while Grinblatt, Titman, and Wermers

[1] Blake, Elton, and Gruber (1993) find no evidence of persistence in a small unbiased sample of corporate-bond funds and some evidence of persistence in a larger survivor-biased sample spanning only 1987 to 1991. They hesitate to conclude that persistence is a general feature of bond funds.

(1995) suggest that active momentum investing by funds produces better fund performance (before expenses and trading costs).[2] Finally, even if we agree to control for momentum in the underlying returns, the most commonly used procedure for doing so might not be precise enough. The factor-model method initiated by Carhart to adjust fund performance for momentum in stock returns employs a winner-minus-loser factor-mimicking portfolio. Fama and French's (1993) finding that their three-factor model cannot fully account for size and book-to-market-equity effects in returns despite two of their factors being based on size and book-to-market equity should give us pause. In sum, these issues combine to undermine our ability to draw clear inferences on performance persistence from the equity-fund results.[3]

Unlike stock returns however, corporate-bond returns do not display momentum. Gebhardt, Hvidkjaer, and Swaminathan (2005) find no evidence of momentum in the returns of high-quality bonds, and we document the same for high-yield bonds.[4] In this study of corporate-bond mutual funds, we examine persistence in fund performance without the confounding influence of momentum in the underlying asset's returns.

We examine the performances of over 1,200 corporate-bond mutual funds from 1990 to 2004. On average, funds trading high-quality bonds generate positive abnormal returns before fees of roughly 3 to 5 basis points per month, depending on the method of performance evaluation. After incurring expenses, high-quality-bond funds significantly underperform benchmarks by roughly 5 basis points per month. The average performance of funds trading high-yield bonds, however, is statistically zero, both before and after expenses. These findings portray a slightly better picture of performance than that typically found in the equity-fund literature, for example by Carhart (1997).

[2]Carhart attributes this disparity in findings to momentum strategies being costly to pursue.

[3]Recent studies of equity mutual funds employ measures of skill other than prior returns to select funds that generate positive alpha. Cohen, Coval, and Pastor (2005), Kacperczyk and Seru (2006), Avramov and Wermers (2006), and Kacperczyk, Sialm, and Zheng (2006) condition their fund selections on different sets of information — a comparison of the holdings of a given fund to those of funds with outstanding performance records, sensitivity of changes in a fund's holdings to changes in analysts' recommendations, business-cycle variations in skill, risk, and risk premia, and the difference between a fund's actual returns and its return implied from its quarterly stock holdings, respectively.

[4]The findings are detailed in the Appendix.

We also find that the top decile of funds over the past year outperform the bottom decile over the next four years. This persistence is driven largely by the loser funds continuing to lose, though we do find evidence of the winners' continuing to win. For example, in high-yield funds, the winners' net returns beat their benchmarks by about 15 basis points in the month following ranking. This winning performance in net returns continues only for a few months though. The short-lived ability of the winner funds to generate positive alpha for their investors mirrors Bollen and Busse's (2005) finding for equity-funds. Persistence in the loser funds' poor performance is however long lasting. In high-quality funds, this sustained losing seems due to expenses and the lack of ability of these fund managers to select bonds. In high-yield funds, the persistent losing of the bottom decile of funds is greater than just their expenses. The consequence of these findings is a persistent spread between the net performances of the prior winners and the prior losers that averages 9 to 18 basis points per month over four years for high-quality funds and from 16 to 26 basis points for high-yield funds, depending on the performance metric and the ranking horizon.

Differences in expenses and portfolio turnover cannot account for this persistent spread between winner and loser funds. Instead, the persistent spread seems due to the skill of the winning fund managers. As further evidence of this skill, we also detect strong persistence in gross (before expenses) performance. Specifically, last year's high-quality before-expenses winner funds beats the market by 4 to 9 basis points per month over the next four years before expenses are borne; the gross performance of last year's high-yield before-expenses winner funds beats the market by 9 to 15 basis points per month over the next four years. These findings indicate that some fund managers are skilled at trading corporate bonds. Their investors, however, do not enjoy a lasting market-beating performance as fees drive multi-year alphas to zero, consistent with a competitive market. These findings collectively suggest that corporate bonds are mispriced, that some managers can identify and exploit these mispricings, and that variation in the skill of bond-fund managers can be detected using prior performance.

We then investigate whether investors are taking advantage of the persistence in performance that we document. We find that bond-fund investors chase prior performance, as equity-fund investors do. However, as many economists recognize, perhaps Edelen (1999) most notably, inflows can hinder fund performance. So chasing prior performance does not guarantee future rewards for investors. For high-yield funds, we find that funds with net inflow over the prior quarter perform better than the funds with net outflow. Moreover, the explanatory power of flow for future returns is subsumed by prior alpha indicating that investors rely on prior performance to predict future performance. That the chasing of prior performance is rewarded in high-yield funds is consistent with the findings of "smart money" by Gruber (1996) and Zheng (1999) in equity funds, which they recognize as a potential explanation for equity fund investors' reliance on actively managed funds despite the fact that such funds on average have difficulty performing as well as stock index funds. The inability of flows to predict future performance in high-quality funds suggests that returns to scale in the high-quality market are more rapidly diminishing.

In addition, Sapp and Tiwari (2004) and Keswani and Stolin (2007) show that the ability of equity-fund flows (the smart money) to predict future performance is strongly related to the momentum in the underlying stock returns. So the literature again has an important result regarding mutual funds which is clouded by momentum in stock returns. In a setting unfettered by momentum in the underlying returns, we find evidence of persistence in mutual-fund performance and of investors benefiting from it.

In the next section, we detail our performance metrics for corporate-bond funds. In section 3, the sample is described. The average performance of the funds is provided in section 4. Section 5 documents persistence in performance, and section 6 examines potential explanations for such persistence. Section 7 finds evidence of investors' chasing prior performance and benefiting from doing so. We conclude the paper in section 8.

2 Performance-Evaluation Methods

In this section, we detail the methods we employ to assess the performances of corporate-bond mutual funds. Since there is no consensus about what methods are best to use, we examine performance using various sets of factors, restrictions on factor loadings, conditional factor loadings, market-timing specifications, and the inclusion of lagged factor premia to accommodate potentially stale pricing.

Essentially, the performance of a corporate-bond fund is evaluated as the risk-adjusted alpha from a multifactor model:

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \epsilon_t \tag{1}$$

where R_t is a given fund's *excess* return in month t over the one-month Treasury-bill rate, F_{kt} is the realized excess return of factor k, β_k is the sensitivity of the fund's returns to factor k, ϵ_t is the error term, and α is the performance metric.

For ease of exposition, we focus our discussions on three of the performance-evaluation models that we employ. The other performance models we consider are described in the Appendix. Findings across the entire set of models are similar to those across the three models we report.

2.1 Two-Factor Model

All bond indices used in this study are provided by Lehman Brothers. They are value-weighted and exclude bonds with less than one-year to maturity. Our two-factor model uses the excess return of the Government index over the one-month Treasury-bill rate (G) and the spread between the return of the investment-grade index (HQ, labeled Credit index by Lehman) and the return of the high-yield index (HY, labeled Corporate High-Yield index by Lehman).

$$R_t = \alpha + \beta_1 G_t + \beta_2 (HQ_t - HY_t) + \epsilon_t \tag{2}$$

2.2 Style Analysis

Our second model is a style-based benchmark similar to that developed by Sharpe (1992). Essentially, a portfolio of style-based assets that best tracks each bond fund is identified, and the return on that portfolio is used as the benchmark for a given fund. The benchmark portfolio of each fund is found by identifying the weights on each asset that minimize the tracking variance.

$$\min_{\beta_k} \mathrm{Var}\left[R_t - \sum_k \beta_k R_t^k\right] \qquad \text{s.t.} \sum_k \beta_k = 1, \beta_k \geq 0 \tag{3}$$

where $\mathrm{Var}[\cdot]$ is the variance operator, R_t^k is the excess return on asset k and β_k is the weight on asset k that minimizes the tracking variance. Sharpe (1992) suggests applying the given constraints on the weights to better mimic the fund's portfolio of assets, as few mutual funds take short positions. The style-based performance metric is then

$$\alpha = \frac{1}{T}\sum_t^T \epsilon_t \tag{4}$$

where T is the number of months available for a given fund and $\epsilon_t = \left(R_t - \sum_k \beta_k R_t^k\right)$

We employ a set of six style-based assets: the Intermediate and the Long-Term Government bond indices, the Intermediate and the Long-Term Investment-Grade bond indices, and the Intermediate and the Long-Term High-Yield bond indices.

2.3 Four-Factor Model

Our third model is based on Elton, Gruber, and Blake's (1995) six-factor model. We exclude the two macroeconomic factors and form the following model.

$$R_t = \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_4 OPTION_t + \epsilon_t. \tag{5}$$

where STK is the excess return on the CRSP value-weighted stock index, $BOND$ is the excess return on the Lehman Aggregate bond index, DEF is the return spread between the High-Yield index and the Intermediate Government index, and $OPTION$ is the return spread between the GNMA index and the Intermediate Government index. All fixed-income indices are again from Lehman Brothers.

We consider a six-factor model that includes the change in the logarithm of the Composite Index of Leading Indicators and the change in the logarithm of the Consumer Price Index as the additional factors. However, given the difficulty in reliably estimating the macroeconomic risk premia (i.e. the estimates are sensitive to the procedure used — maximum-correlation portfolios versus cross-sectional regressions) and since performance results differ little when using the additional two factors, we rely on the four-factor model in our discussions.

3 Sample of Corporate-Bond Funds

The CRSP Survivor-Bias-Free U.S. Mutual Fund Database includes bond mutual funds. Our sample spans January 1990 to December 2004, as objective codes for funds are not widely available before 1990. From the annual summary data, we select funds whose objective codes indicate that the fund concentrates its holdings in corporate bonds. Specifically, we select funds with Wiesenberger codes CBD or CHY, or with ICDI codes BQ or BY, or with Strategic Insight codes CHQ, CHY, CGN, CIM, CMQ, or CSM. The Weisenberger and Strategic Insight codes are available through 1995; ICDI codes are available from 1993 on. The sample is divided into those funds concentrating in high-quality bonds and those concentrating in high-yield bonds.[5] Finally, we require funds to have at least 24 return observations so that the performance-evaluation models can be reasonably estimated. (For the conditional versions of the six-factor and style-based models, we require at least 36 observations.) The 24-month requirement imparts no noticeable survivorship bias on performance. Specifically, the alpha of the equally

[5]High-quality funds have objective codes BQ, CHQ, CBD, CMQ, CGN, CIM, or CSM; high-yield funds have CHY or BY.

weighted portfolio of all funds with at least 24 months of returns is nearly identical to the alpha of the equally weighted portfolio of all funds.[6]

No other data filters are imposed on the sample. However, we find that removing the funds with lower than $10 million dollars of total net assets last year, or with greater than 10% of their holdings in equity last year, or with an R^2 from a given factor model lower than 0.20 does not affect the overall performance findings. Also, for fund returns net of expenses, we examine average performance and persistence at the share-class level, but examining at the fund level (with asset-weighted returns) produces similar findings. For returns gross of performance, our analyses are at the fund level.

Table 1 provides some summary characteristics for the samples of high-quality (Panel A) and high-yield bond (Panel B) funds as well as the various factors we will employ to evaluate fund performances (Panel C). The statistics (pooled across fund/share classes) are reported for three five-year subperiods and for the whole sample as well. We first see that the number of fund entities increases explosively across the sample period. For high-quality funds, we go from 1,572 in the 1990 to 1994 period to 5,492 in the 2000 to 2004 period. The number of high-yield fund entities increases from 478 in the first subperiod to 2,009 in the last. We can also see that the average and standard deviation of return for high-quality funds are relatively stable across the sample period, whereas these measures change markedly for the high-yield funds across the subperiods.

Panel C of Table 1 reports return properties over the full sample period for the seven factors we use in the various models of performance evaluation. The Aggregate and Government indexes deviate little from each other, with the High-Quality index relatively close. The High-Yield index though has a standard deviation of return (12.55% per year) that is roughly double that shown by the three other indexes, and a slightly larger average return. The Stock index has the highest standard deviation of return, but

[6]As an assurance check on the fund returns reported by CRSP, we examine a subsample of funds on the April 2003 edition of Morningstar Principia. For the 74 funds in March 2003 in the lowest decile of alphas over the prior twelve months, 71 are listed in Morningstar. The monthly returns from March 2000 to March 2003 on CRSP and Morningstar are within one basis point for 96% of the available 1770 fund-month observations. For the 22 funds in January 1994 in the highest decile of alphas over the prior twelve months, 15 are listed on the April 2003 Morningstar disc. The monthly returns from January 1992 to January 1994 on CRSP and Morningstar are within one basis point for 87% of the 375 fund-month observations.

its mean return is relatively low at only 7.35%. The two remaining factors are Default and Option which measure return spreads across appropriate indexes. As such, their average returns are small, but the Default index does display a rather large standard deviation of return of 12.35%.

Table 2 provides several characteristics of the funds over the sample period, namely mean ages, sizes (TNA), turnovers, loads, and expense ratios. We also report the mean portfolio weights across a number of asset classes. Corporate and government bonds together comprise roughly 80% of high-quality funds, while as expected, corporate bonds alone comprise over 80% of the holdings of high-yield funds. The remaining bond and stock categories receive little weight. In fact, cash is the next largest category for both high-quality and high-yield funds, roughly 7% and 5% respectively. Although we consider performance evaluation based on asset classes other than government and corporate bonds, as discussed in sections 2.3 and A.3 of the Appendix, we can surmise from Table 2 that accounting for the performances of other classes will not materially affect our results.

4 Evaluating Average Performance

Cornell and Green (1991), Blake, Elton, and Gruber (1993), and Elton, Gruber, and Blake (1995) conclude that bond funds generally underperform benchmarks net of expenses. However, none of these studies has a sample size of corporate-bond funds greater than one hundred or data later than 1991 (prior to the explosion in the number of funds shown in Table 1 and in capital invested).

4.1 Net of expenses

We tabulate performances based on the two-factor, the style, and the four-factor models. The Appendix details the other models we consider (namely, a six-factor model as well as the conditional, the market-timing, and the stale-pricing variants of the three base models we tabulate). The overall findings are similar across these other models.[7]

Table 3 provides the distribution of alpha within high-quality (HQ) and high-yield (HY) funds for the three baseline factor models from 1990 to 2004. As shown in Panel A, the mean and median performances of the HQ funds are negative, ranging from -0.06% to -0.02% per month across the three models. We employ an equally weighted portfolio (EW) of all available HQ funds each month to provide statistical inferences on the average fund's performance. The alpha for this calendar-time EW portfolio ranges from -0.05% to -0.03% and is statistically negative using the four-factor and the style models.

For HY funds, the evidence tilts more towards zero abnormal performance. The mean and median alphas range from -0.07% to 0.00% per month across the three models. The alpha of the calendar-time EW portfolio of HY funds ranges from -0.04% to -0.01%, but no estimate is significantly negative.

Table 3 also gives the fraction of funds with positive or negative alphas. The tails of the cross-sectional distribution (ignoring cross correlations) are fat, with far greater than 2.5% of the funds in the upper and lower tails for each performance model. This observation foreshadows the later finding that performance of these funds persists, in that there are true deviations from zero alpha. Panel B shows that the pairwise rank correlations across the three models are high, ranging from 0.82 to 0.95, foreshadowing that our persistence findings are invariant to the performance model employed.

For those readers interested in the investors' experience in aggregate, the value-weighted alphas (not in the tables) for high-quality funds are two to three basis points

[7] Here we provide a few observations regarding the other performance models. One, the lagged factors in the stale-pricing models generally do not load, providing little evidence of pervasive stale pricing in the bond funds. Two, for both the Treynor-Mazuy and Henriksson-Merton timing parameters, the evidence of market timing is statistically weak and there is a tendency for the point estimates to be negative. For comparison, equity mutual funds display, if anything, this same tendency toward perversely negative market timing, as Ferson and Schadt (1996) for example find. Chen, Ferson, and Peters (2005) examine the timing abilities of fixed-income fund managers (excluding only money-market and municipal-bond funds) and find a modest tendency for negative timing, even after controlling for a myriad of potential issues such as convexity in bond returns, managers' conditioning on public information, and stale pricing. In light of the inability of their improved tests to alter the evidence on timing, we do not pursue further enhancements of the timing models.

per month greater than the equal-weighted alphas in Table 3, reflecting the positive size effect shown in later tables. The value-weighted alphas for high-yield funds differ little from the equal-weighted funds, reflecting the lack of any size effect across high-yield funds.

Overall, the picture of the average performance of HQ funds is tilted below zero, while the average performance of the HY funds is statistically zero. The set of evidence suggests that HY fund managers are better able to offset the expenses charged to their investors. The HY alphas contrast even more strongly with the evidence of strong underperformance in the average net returns of equity funds provided by Carhart (1997) and others.

4.2 Gross of expenses

By considering the performance of funds before their expenses are taken out, we can better comment on the abilities of fund managers (and presumably other investors) to identify and exploit profit opportunities in corporate bonds. In short, we employ gross returns to inform us about the skill of fund managers. Can these fund managers beat the market?

Panel A of Table 4 provides performance statistics of HQ funds gross of expenses, where annual expenses divided by 12 are added to net returns. We see that the mean and the median estimates of the gross alphas across funds are positive using the three performance models, ranging from 0.01% to 0.05% per month. The gross alphas for the EW portfolio of HQ funds range from 0.03% to 0.05% across the models with all three t-statistics greater than 2.0. In short, removing fund expenses (but not transaction costs) from fund returns provides evidence that managers of HQ corporate-bond funds are able to beat the market on average by a handful of basis points per month. As noted in the previous section however, these managers do not beat the market by enough to cover their expenses.

Panel B of Table 5 shows the performance of the HY funds gross of expenses. The mean and median alphas range from 0.04% to 0.10%. The alpha estimates of the EW portfolio of HY funds ranges from 0.06% to 0.08%, but none are statistically significant. In short, the average before-expenses performance of high-yield funds is statistically indistinguishable from zero due to the large variability in alpha. We do not detect that the average high-yield manager selects bonds that produce reliably positive alpha.

5 Persistence in Performance

We now consider whether the best corporate-bond funds in the past continue to perform well in the future and whether the worst funds in the past continue to be perform poorly in the future. We examine persistence in both net and gross performance, separating the performance of the fund investors from the skill of the fund manager.

Since the results of the prior section indicate that performance evaluation is primarily independent of model selection, we make our task more manageable by reducing the models we consider in this section. To rank funds, we use the two-factor model of equation (2), the four-factor model of equation (5), and the style-based model of equation (4). To evaluate post-ranking performance, we use all three base models. Using models other than the one used to rank the funds mitigates potentially spurious persistence in performance that can be induced by the ranking model's misspecification of expected returns for any individual fund. We consider various horizons for the ranking and the holding periods. For ranking periods, we examine 12, 24, and 48 months. For holding periods, we examine 1, 3, 12, 24, and 48 months. For brevity, we tabulate only the 12/1 and 12/48 combinations of ranking/holding periods, which succinctly convey the overall results.

To examine holding-period performance over windows greater than one month, we employ a calendar-time procedure, to avoid overlapping the returns and the potentially severe serial correlation that overlapping produces. For example, when examining the future 48-month holding-period performance of the funds that are winners (top-decile) over the prior 12 months, we identify the portfolios of funds in calendar-month τ that are determined to be winners at each month-end of the prior 48 months. The winner portfolio from month $\tau-1$ is in the first month of its holding period; the winner portfolio from month $\tau - 2$ is in the second month of its holding period, and so on, all the way back to the winner portfolio from month $\tau-48$ which is in the forty-eighth month of its holding period. We equally weight the returns in month τ for these 48 portfolios. This equally weighted return captures the performance of all funds in calendar-month τ that are currently in their 48-month window. The procedure is rolled forward one calendar month and an equally weighted return for the next month is recorded. The resulting time series of returns is then analyzed using the factor models.

5.1 High-quality funds

5.1.1 Net returns

Each month, we rank all HQ funds based on their performances over the prior 12 months using each of the three models, with the factor loadings estimated over the prior 24 months. Panel A of Table 5 employs the two-factor model as the ranking metric and presents the post-ranking alphas of the top decile of funds (winners), the bottom decile of funds (losers), and the spread between the two (W-L). We see on the left side of Panel A that the equally weighted portfolio of 12-month HQ winners determined by the two-factor model has alphas during the first month following ranking that are on average slightly positive, though not statistically so, varying from 0.01% to 0.04% per month across the three performance metrics. Increasing the holding period to forty-eight months does not change the picture; winning funds over the prior twelve months, using this ranking measure, do not continue to generate positive alphas in the future.

Continuing with net returns, we see that ranking with the four-factor model and especially with the style model produces stronger evidence that winning funds continue to win, though this persistence is short-lived. The left side of Panels B and C show that winners based on these other models produce alphas in the first month between 0.03% and 0.07%, with all but one estimate providing evidence of a statistically positive alpha. Untabulated results show the evidence of positive alpha remaining for a few months. This finding is similar to that of Bollen and Busse (2005) for equity funds. They find that winner equity funds continue to generate positive alpha over a short time only, in their case just from one quarter to the next.

The performance persistence of the loser funds is also given in Table 5. On the left side of Table 5, the losers continue to generate negative net-return alphas across all future horizons examined. The magnitude of their underperformance in the post-ranking periods varies from -0.17% to -0.08% per month across all combinations of ranking and evaluation metrics, with t-statistics that are all below -2.65. The finding that loser funds continue to strongly underperform is a robust feature of corporate-bond funds. The persistent and long-lived poor performance of the loser funds results in a strong and persistent disparity between the winner and the loser funds. Table 5 shows that the winner-minus-loser (W-L) alphas are at least 0.09% per month across metrics and holding periods, with t-statistics all above 4.0.

Carhart (1997) and others find that losers continue to lose in equity mutual funds, and Christopherson, Ferson, and Glassman (1998) find such continuation for equity pension funds as well. We examine potential reasons for this pattern in corporate-bond mutual funds later. It is sufficed to say for now that, for HQ funds, expenses can account for most of the negative alphas in the loser funds. Interestingly however, expenses cannot explain the persistent spread between the winners and the losers, as the expenses of these portfolios differ only slightly.

In short, we find evidence that HQ winners from last year continue to beat their benchmarks for a few months. In contrast, the HQ losers from last year, or even the prior four years, continue to lose sizably over the next four years.

5.1.2 Gross returns

Turning to persistence in gross returns, the right side of Table 5 provides the gross (before expenses) performances of last year's winners and losers, with rankings also determined using gross returns. Last year's winning managers continue to beat the market for at least 48 months. The alphas are above 8 basis points per month across all metrics in the first month of the holding period and decline only to a still-significant

4 basis points per month over 48 months. This finding is noteworthy and suggests that some managers can consistently beat the market in their trading of corporate bonds.

On the loser side interestingly, the 4-factor and style models, regardless of the ranking metric, tend to indicate that losing managers continue to generate negative alpha in month 1. We do not expect managers to be systematically wrong in their bond selections however. The underperformance dissipates by month 3 (not in tables).

5.2 High-yield funds

5.2.1 Net returns

Table 6 is similar to Table 5 but for high-yield funds. On the left side, we see that ranking with net returns over the prior 12 months using the two-factor model (Panel A), the four-factor model (Panel B), or the style model (Panel C) identifies short-lived persistence in the performance of winner funds. Winners over the prior twelve months generate alphas that are at least 0.10% in the first month after ranking, with every t-statistic above 2.0 except for two of the alphas in Panel C, and one of those is 1.65. As is the case for HQ funds, 12-month HY winners' alphas tend to dissipate quickly. Untabulated results show that the evidence of positive alpha for the winners is gone by month 3, though the point estimates typically remain above 0.05% per month. In short, persistence in the good performance of winner funds is more more evident in HY funds, but such persistence remains short-lived.

Similar to the HQ results of Table 5, we see that HY losers continue to lose over the 48 months following portfolio formation, regardless of the ranking metric and holding period. The underperformance is striking, ranging from -0.23% to -0.13% per month for forty-eight months. As we will shortly see, this underperformance in net returns is due to more than just expenses.

5.2.2 Gross returns

Turning to the persistence in gross performance of HY funds, we see on the right side of Table 6 that HY managers with the best before-expense performance last year continue to beat the market before expenses for many years. Their alphas in month 1 are at least 18 basis points per month and all are statistically significant. By month 48, their alphas are still at least 9 basis points per month, with only one t-statistic less than 1.65. These high-yield fund results echo the noteworthy finding from the high-quality funds that some money managers are able to persistently beat the market with their trading of corporate bonds.

Table 6 also shows the curious result that loser managers continue to underperform the market in the future. Their alphas in month 1 are all statistically significant and lower than -0.16%. This underperformance persists for at least 12 months according to the two-factor and four-factor models. This persistence in poor performance when using returns gross of expenses seems perplexing, since we do not expect managers to consistently err by picking negative-alpha bonds. We consider this result further in the next sections.

6 Can we explain the persistence in performance?

In this section, we investigate several potential explanations for the persistence in performance that we see in the prior section. For the persistence in HQ losers' returns net of expenses, we consider whether the expense ratios of loser funds account for their underperformance. The persistence in the HY losers exists for many months even in the returns gross of expenses so we employ turnover as a proxy for trading costs and examine as best we can the extent to which trading costs can account for the sustained losing. Last, we consider whether stale pricing of funds (or the underlying securities) can account for some of the persistence in performance.

6.1 Characteristics of Lagged-Performance Deciles

Panel A of Table 7 provides the means of several characteristics for each decile of funds ranked on performance over the prior 12 months using the two-factor model. Maximum load, age, and log(TNA), are sampled at the end of the ranking period. Expenses, annual turnover, raw return, and the two-factor alpha (loadings estimated over prior 24 months) are for the month after the ranking period. Our reason for examining expenses and turnover contemporaneously to returns is to determine whether these measures can explain, not predict, persistence.

First, we can see in both Panels A and B of Table 7 that α_{t+1} declines monotonically as the deciles decline from winners to losers. This reinforces the strength of the persistence in performance we document in the prior sections.

In Panel A, we also see that expense ratios (expressed per month) vary only slightly across the deciles. More importantly, the loser funds do not have substantially larger expenses than the winner funds, only a 0.03% spread per month. The magnitude of this difference is far smaller than the differences in alphas between winners and losers shown in Table 5, which are at least 0.09% per month even after forty-eight months. Panel B of Table 7 shows that expenses differ even less across HY winners and losers, only a 0.02% spread per month. In sum, expenses are capable of explaining little of our findings. In fact, only the sustained poor performance of the HQ losers seems largely attributable to expenses. The spread between winners and losers for both HQ and HY funds, the ability of HQ and HY winners to continue winning, and the finding of HY losers continuing to lose must be due to other reasons. One possibility for the poor performance of HY losers is that their trading costs are higher. Without data on transactions, however, we can only use portfolio turnover as a proxy for trading costs. Panel A of Table 7 shows that HQ winner funds have much higher turnover in the coming months than other funds, 206% per year on average versus the 155% averaged across the lower deciles (not in table). This finding loosely suggests that winner HQ funds are more skilled as these funds perform best despite trading most often and presumably incurring greater trading costs. This finding is unique to HQ funds. For HY funds, Panel B shows that turnover is on average lower and less variable across the performance deciles.

The remaining columns in Table 7 provide means of size, maximum load, and age. For both HQ and HY funds, we see little variation across lagged-12-month deciles for most of these characteristics, especially across HY deciles. Interestingly, size seems positively related to performance for HQ funds, which we discuss further in the next section.

6.2 Regression evidence

To formally see how these characteristics relate to performance, we estimate each month a cross-sectional regression of risk-adjusted returns in month t on lagged characteristics. Specifically, we examine how future 12-month performance relates to expenses, turnover, size, the existence of a load, and past 12-month performance of funds. Since we wish to examine future performance over a window longer than one month (specifically 12 months), we employ a procedure that is akin to the calendar-time portfolio method used in section 5. The benefit of such a procedure is that we avoid overlapping both sides of the regression which would induce strong serial correlation in the time-series of cross-sectional coefficient estimates, leaving us with concerns about our ability to accurately estimate the standard errors.

For example, let January 1992 be month t. We regress the cross-section of the one-month risk-adjusted return in January 1992 (using factor loadings over $[t-11, t+12]$) on lagged alpha over $[t-12, t-1]$ (using factor loadings over $[t-24, t-1]$) and the characteristics sampled at month $t-1$. Call this set of estimated coefficients $\mathbf{B}_{t1}$. Using the same left-hand side variable as before and rolling the right-hand side variables back one period, we next regress the risk-adjusted return in the month of January 1992 on alpha over $[t-13, t-2]$ (using loadings over $[t-25, t-2]$) and the characteristics sampled at month $t-2$. Call this set of estimated coefficients $\mathbf{B}_{t2}$. Roll the right-hand side variables back one more period to obtain $\mathbf{B}_{t3}$. Since the goal is to examine future performance over the next 12 months, we roll back the right-hand side variables one month at a time until we reach $t-12$. So the last regression using the January 1992 risk-adjusted return on the left-hand side regresses January 1992 performance on alpha over $[t-23, t-12]$ and the characteristics sampled at month $t-12$. These twelve regressions for January 1992 produce $\mathbf{B}_{t1}, \mathbf{B}_{t2}, \ldots, \mathbf{B}_{t12}$. The last step for January 1992 is to average the twelve coefficients to produce $\mathbf{B_t}\left(= \frac{1}{12}\sum_{k=1}^{12} \mathbf{B}_{tk}\right)$ — a single, summary measure of how lagged 12-month performance relates to future 12-month performance using just the month of January 1992 as the future return.

Roll the left-hand side forward to February 1992 and repeat the process of running twelve regressions for that month to obtain a second value for $\mathbf{B_t}$. Rolling forward through the sample period produces a time series of $\mathbf{B_t}$. Finally, we calculate a t-statistic using the standard error of the time series of each coefficient. The overlapping of the right-hand-side variables can produce a mild serial correlation in the time series of $\mathbf{B_t}$ so we employ the variance estimator of Newey and West (1987) with six lags, which is robust under serial correlation and heteroskedasticity.[8] Finally, note that expenses and turnover are sampled from the upcoming fiscal year end (as in Table 7) and as such are contemporaneous with the future 12-month performance that we seek to explain.

We examine two alternative specifications of fund performance in the regression analyses: the two-factor model and the style model. In addition to the 12/12 (past window/future window) regression method outlined above, we also consider 12/24, 48/12, and 48/24 specifications. We tabulate the 12/12 and 48/12 results for both the two-factor and style models. The tests on 24-month holding periods, as well as those examining gross returns, reveal similar findings.

We see first in Panel A of Table 8 the regression evidence of persistence in the abnormal performance across HQ funds, mirroring the (W-L) portfolio evidence in section 5. Across regression models, the coefficients on lagged 12-month performance ($\alpha_{[t-12,t-1]}$) and lagged 48-month performance ($\alpha_{[t-48,t-1]}$) are all positive, with all t-statistics above 3.0. Hence, performance over the prior year and performance over the prior four years, respectively, are strongly related to next year's performance.

Only two other variables display explanatory power for future returns. Expenses are negatively related to future performance, and log(TNA) is positively related. The finding for expenses is a common one in the equity-fund literature, though the point estimates on expenses in HQ funds are lower. Carhart (1997) finds the impact of expenses on the performance of equity funds to be greater than one-to-one. The coefficients in

[8]Using zero or twelve lags does not affect our findings.

Panel A vary from -0.44 to -0.69 and are at least two standard deviations from one. This finding of a less than one-to-one impact on expenses is consistent with some managerial skill on average in the HQ funds. For log(TNA), we see that larger HQ funds perform better. This finding is unique to bond funds. Chen, Hong, Huang, and Kubik (2004) find that fund size is negatively related to future performance (controlling for family size). Carhart (1997) finds an insignificant relation between size and performance in equity funds. The size result for HQ funds provides cursory evidence against the notion that performance deteriorates as size increases. However, Panel B shows no relation between size and performance for HY funds. Further examination of this result in future research seems warranted.

Panel B of Table 8 also shows that abnormal performance persists strongly across HY funds, again lasting several years. Both $\alpha_{[t-12,t-1]}$ and $\alpha_{[t-48,t-1]}$ have t-statistics greater than 3.0. Interestingly, expenses are negatively related to performance in the presence of $\alpha_{[t-12,t-1]}$ but not $\alpha_{[t-48,t-1]}$. One potential explanation is that expenses are a function of long-run performance. The remaining characteristics (turnover, load, and age) display little evidence of a cross-sectional relation to either HQ or HY performance. In short, the persistence in the cross section of fund performance for both the HQ and the HY funds are unexplained by expenses and trading costs, consistent with Table 7.

6.3 Stale Pricing

Another possible driver of persistence in performance is stale prices. Corporate bonds are commonly viewed as less liquid than stocks due to their less frequent trading. If a bond trades infrequently, its prices can be (spuriously) slow to incorporate new information, which can produce continuation in bond returns as prices adjust over time. Getmansky, Lo, and Makarov (2004) provide a useful discussion of illiquidity and return smoothing, both inadvertent and possibly deliberate, in the hedge-fund industry. Also, Chandar and Bricker (2002) provide evidence of closed-end funds' valuing their illiquid and nontraded securities, which they term "restricted," to maximize the long-term probability of exceeding a benchmark. For example, these funds report lower values for their restricted securities when their unrestricted securities perform either extremely well or extremely poorly, and they report higher values for their restricted securities when their unrestricted securities are performing just below their benchmarks.

In our setting however, it is important to remember that most of the persistence we are detecting lasts for years. Specifically, the performance of winners and the spread between winners and losers using gross returns persists for over four years. Stale prices can potentially generate only short-term effects, as the resolution of the staleness should rarely take more than a couple of months. Nevertheless, we examine the issue of stale pricing and its potential effects on fund performance.

First, we examine fund performance net of expenses by modifying our models to include one-month-lagged factors. Although we earlier find little unconditional support for using the lags, we examine here if conditioning on winner and loser status generates greater exposure to the lagged factors. The specifications that we consider are combinations of the following: (i) ranking method — two-factor or style-based performance (with no lagged factors), (ii) ranking period — 12 or 48 months, (iii) holding period — 1 or 48 months. To evaluate the post-ranking performance, we include in the corresponding ranking model the one-month lagged factors. The point estimates and significance levels on the winner and loser alphas from Tables 5 and 6 are affected little.

These results suggest that stale pricing of *systematic* information is not a large concern for our persistence findings. We further examine stale pricing by focusing on *idiosyncratic* information. We examine the standard deviations and the serial autocorrelations in the factor-adjusted returns of winner and loser funds. Ranking funds each month t based on their two-factor performance over the prior 12 months, the standard deviations of factor-adjusted returns (using the three base models) are estimated for each winner and loser fund over months $[t+1, t+24]$. The means of the standard deviations are notably higher for the winner and the loser deciles. For example, using the two-factor model, winner and loser estimates of standard deviations of residual returns are 0.45% and 0.44% per month, while other deciles are clustered around 0.30%. These cursory results suggest that winner and loser funds are less exposed to the stale pricing of idiosyncratic information, as the slow updating of price shocks would reduce return volatility. Moreover, the average serial autocorrelation (up to three lags) in the factor-adjusted returns across winner funds and across loser funds over $[t+1, t+48]$ (or over $[t+1, t+24]$) are not above 0.10, suggesting that stale pricing of idiosyncratic news is not a persistent feature of these funds.[9] In short, without detailed holdings data, we find little evidence that stale pricing is contributing materially to our results.

6.4 Within-family subsidization

Gaspar, Massa, and Matos (2006) provide evidence of fund families' strategically transferring performance across their funds, raising one fund's performance at the expense of another. For example, they find that families allocate more underpriced IPO stocks to their higher valued (higher fees and higher past performance) funds. Gaspar, Massa, and Matos also offer cursory evidence that families with higher performance differences between their higher and lower valued funds seem to engage more in opposing trades whereby the higher valued funds trade against the lower valued funds. To examine if such preferential behaviors within a fund family might contribute to our findings of persistence in fund performance, especially to the sustained poor performance of the loser funds, we include family dummy variables in the regressions of Table 8 (and in the analogous but not tabulated regressions using gross performance instead of net). First, the inclusion of family fixed effects does not affect the inferences regarding persistence in performance. Second, the point estimates suggest that a large portion of the variation driving persistence in performance is within families.[10]

[9] Interestingly, serial correlation for the HY winners and losers are roughly 0.30 when examining the factor-adjusted returns at the portfolio level using equal weights. Other deciles display similar fund-level and portfolio-level autocorrelations, yet the winners and losers are the only deciles to display high autocorrelations at the portfolio level.

[10] In addition, the inclusion of the family dummies removes the positive size effect in HQ funds shown in Table 8.

7 Smart Money

Given our findings of persistence in the performance of corporate-bond funds, we now turn our attention to whether investors take advantage of this persistence when selecting funds for investment. Of course we are now exclusively concerned with returns net of expenses since we are focusing on the perspective of the fund investors. The previous sections show that the ability of winning funds to continue to win net of expenses is short-lived. For the losing funds, however, their poor performances continue for years. Although these open-end mutual funds cannot be sold short, investors can still benefit from the losers' persistence by avoiding the worst funds. In this section, we consider whether investors chase performance and whether they move in and out of the right funds, that is, into the funds that will reap positive alpha and out of the funds that will suffer negative alpha.

Gruber (1996) and Zheng (1999) provide evidence that investors in equity mutual funds are able to select the better-performing funds. They find that the funds with net inflow outperform the funds with net outflow for at least three months. Gruber labels this phenomenon as "smart money." However, Sapp and Tiwari (2004) find that controlling for the momentum in the underlying stock returns eliminates the evidence of smart money. Using the Carhart (1997) four-factor model over 1970 to 2000, they document that the performance of equity funds with net inflows last quarter is no longer different from the performance of the funds with net outflows. Keswani and Stolin (2007) add to this literature by showing the evidence of smart money to be strengthening since 1990 in both U.S. and U.K. equity funds, even after controlling for momentum. Keswani and Stolin find that momentum is still strongly related to the finding of smart money though, returning us to the points in the Introduction regarding the ambiguity in assessing the effects of momentum on persistence in fund performance.

In this section, we examine whether "smart money" exists in corporate-bond mutual funds. Since returns of corporate bonds do not display momentum, we avoid the confounding influence of momentum on the tests and further contribute to the evidence on this phenomenon. First, we briefly document that flows of corporate-bond funds tend to chase prior performance. Then, we ask whether funds with inflow enjoy better returns than funds with outflow.

7.1 Do flows chase performance?

Sirri and Tufano (1998), Chevalier and Ellison (1997), Del Guercio and Tkac (2002) and others find that flows of assets under management at equity funds chase prior performance, with the best-performing funds receiving the lion's share of the flow. We measure percentage flow in month t as:

$$Pflow_t = \frac{TNA_t - TNA_{t-1} \times (1 + r_t) - MGTNA_t}{TNA_{t-1}} \tag{6}$$

where TNA_t is a given fund's total net assets in month t, r_t is the fund's net return, and $MGTNA_t$ is the increase in TNA due to fund mergers. To examine how flow relates to prior performance, we follow Sirri and Tufano's (1998) procedure and first determine in month t the percentile rankings of each fund based on performance according to the 2-factor model over $[t-12, t-1]$, with factor loadings estimated over $[t-24, t-1]$. We then estimate the following linear regression piecewise over quintiles of lagged performance. To do so, we form five quintile-based explanatory variables, Q1 to Q5. For $i = 1$ to 5

$$\mathrm{Q}i \quad = \quad \begin{cases} 0 & \text{if } rank < \frac{i-1}{5} \\ \min\left(rank - \frac{i-1}{5}, 0.20\right) & \text{if } rank \geq \frac{i-1}{5} \end{cases}$$

The coefficients on these measures captures the sensitivity of flow to prior performance within quintiles 1 to 5 respectively, with 1 as the lowest quintile. We also consider a vector of characteristics sampled at $t-1$ comprised of log(TNA), 12b-1 fees, expenses minus 12b-1 fees (non12b-1), and load dummy. The regression is estimated each month, and standard errors are estimated from the monthly time series of coefficients using Newey and West's (1987) procedure with six lags. Following Huang, Wei, and Yan

(2006), we delete the top and the bottom 2.5% of the flow observations to remove extreme erroneous data on flows.

Table 9 shows the results of these regressions. For HQ funds, we see the convexity at the upper end of prior performance, which is a well-documented phenomenon in equity funds. The sensitivity of flows to lagged performance is at least three times greater in the top quintile than in the middle quintiles. HY flows display an even greater convexity at the top-end of prior performance. Interestingly, at the bottom-end of lagged performance, both HQ and HY flows display strong sensitivity to performance. This finding that assets flow out of the worst-performing corporate-bond funds differs from the equity-fund findings, where prior studies detect little, if any, punishment for the worst funds. In short, flows of assets in corporate-bond funds chase past performance, moving out of loser funds and into winner funds. Combining this with the evidence in sections 5 and 6 that relative performance across HQ funds and across HY funds persists into the future, we have the potential for "smart money" to use prior performance as a means to identify better funds.

7.2 Do investors benefit from chasing performance?

We first examine if smart money exists in bond funds from a portfolio perspective, as done by Gruber (1996) and Zheng (1999). We separate funds with net inflow over the prior three months from funds with net outflow and evaluate these two portfolios over future holding periods (using calendar-time portfolios).

Panel A of Table 10 provides the performances of equal-weighted and flow-weighted portfolios formed each month from HQ funds with net inflow over the prior three months and of equal-weighted and flow-weighted portfolios formed from HQ funds with net outflow. The portfolios in Panel A are held for 3 months or 12 months, and performance is determined using the 2-factor and style models of expected returns. As before, we use calendar-time portfolios, averaging the returns of the three portfolios in each calendar month that are in months 1, 2, and 3 of their holding periods. For HQ funds we see no evidence of "smart money." The spread in performance across the inflow and outflow funds is statistically zero across weighting schemes, performance models, and holding periods. Despite the fact that relative performance persists across HQ funds and that HQ flows chase performance, inflows do not enjoy better returns than outflows. One possibility is that flows drag on performance through increased trading costs or through the increased difficulty of the manager to selectively invest the new capital.

For HY funds, Panel B reveals a different story. The inflow portfolio outperforms the outflow portfolio by about 6 basis points per month over the next 3 months. In short, a subset of HY investors is able to identify the funds that will perform better in the future. The results from the 12-month holding period show that the ability of investors to predict performance remains through month 12, particularly when relying on the equal-weighted results.

While it is interesting for future research to determine why this pattern exists for HY funds but not for HQ funds, the point for now is that inflows outperform outflows in a market without momentum in the underlying securities' returns. This finding gives more credence to the existence of smart money in mutual funds.

We now examine whether smart money is relying on any more than just prior performance when allocating flows across funds. To do so, we estimate the following regression each month.

$$\begin{aligned}\hat{\alpha}_{t+k} &= b_0 + b_1 Dflow_{[t-3,t-1]} + b_2\hat{\alpha}_{[t-3,t-1]} + b_3\hat{\alpha}_{[t-12,t-4]} \\ &\quad + b_4\hat{\alpha}_{[t-24,t-13]} + \mathbf{cX_{t-1}} + \epsilon_t \qquad (7)\end{aligned}$$

where α_{t+k} is the future abnormal return using either the 2-factor model or the style model, $Dflow_{[t-3,t-1]}$ is dollar flow for a given fund over the prior three months (calculated using only the numerator of equation (6)), and $\mathbf{X_{t-1}}$ is a vector of characteristics sampled at month $t-1$ comprised of log(TNA), expenses, load dummy, and turnover.[11] We use three past horizons of α on the right-hand side to address if flow provides any information regarding future performance beyond the information contained in past

[11] Using percentage flow does not alter our findings.

performance. In other words, we compete flow with past performance as predictors of future performance. The three windows of past performance that we examine are $[t-3, t-1]$, $[t-12, t-4]$, and $[t-24, t-13]$. The prior quarter is used to directly compete with the horizon of flow. The other windows are admittedly arbitrary and are meant to capture the relations between flow and lagged performance captured in Table 9. To examine future periods of returns on the left-hand side that are longer than one month, we again employ the procedure detailed in section (6.2) that avoids overlapping the left-hand side variable. The two future periods we consider for α_{t+k} are the next 3 months and the next 12 months, as in Table 10. Standard errors are estimated from the monthly time series of coefficients using the procedure of Newey and West (1987) with six lags.[12]

Table 11 reports the regression results for performance based only on the two-factor model. The findings concerning the performance-flow relation are unchanged by using the style model. For both HQ and HY funds, the regression results reveal no relation between 3-month flow and future performance, controlling for past performance. Based on the results in Table 10, we do not expect to see a relation for HQ funds. However, for HY funds, the explanatory power of flow for future returns documented in Table 11 is subsumed by prior performance. In untabulated regressions *excluding* prior performance, flow predicts future performance with t-statistics greater than 2.0 for both the next three months and the next twelve months. Hence, smart money in HY mutual funds relies on prior performance to select funds. Whether we should consider reliance on prior performance to be "smart" or not is a difficult issue in our opinion. Some may require investors to use more complex information before labeling investors as smart. Our findings simply indicate that HY fund investors chase performance profitably.

8 Conclusion

Using a large sample of mutual funds which invest primarily in corporate bonds, the average net performance of corporate-bond funds is a few basis points per month below

[12]Using zero or twelve lags does not affect the findings.

zero, while the average before-fee performance is a few basis points per month above zero. These findings suggest that fund managers are able to beat the market with their selection and trading of bonds, but these rents are not passed along to their shareholders. Moreover, the ability of the most skilled managers to beat the market persists for years in their before-fee performance and even for several months in their net performance. On the other hand, the poor performance of the worst funds persists for years in net performance and, curiously, even persists for a few months in before-fee performance.

Our findings of persistently good performance by the winner funds before-expenses speaks to the pricing efficiency of the corporate-bond market. The effects of the opaqueness of this dealer-driven market have long been questioned.[13] Madhavan (1995) and Bloomfield and O'Hara (1999) find that the informational efficiency of prices is hindered when dealers do not disclose trades. The extent to which opaqueness relates to persistently good performance by the winner funds is an interesting issue to pursue.

In addition, we find that high-yield fund investors select funds based on prior performance and enjoy positive alpha from this strategy. While high-quality fund investors also select funds based on prior performance, they do not realize profits from performance chasing. Why inflows preclude positive alpha in the high-quality funds but not in the high-yield funds is a question for further research, as is the finding that larger high-quality funds tend to outperform smaller high-quality funds.

The findings of performance persistence in these mutual funds and of investors taking advantage of the persistence ("smart money") are particularly useful in light of the evidence that these two phenomena in equity funds are strongly related to momentum in the underlying stock returns. Since the source of the return momentum remains unclear, the evidence of performance persistence and of smart money in equity funds remains unclear (e.g., see Sapp and Tiwari (2004)). Given that corporate bond returns do not display momentum, our results show that these phenomena exist in a market without the benefit of return continuation in the underlying securities.

[13]The Securities and Exchange Commission's recent charge to increase the transparency of the corporate-bond market was taken up by NASD through its Trade Reporting and Compliance Engine (TRACE), instituted on a limited basis in 2002.

A Appendix

A.1 No momentum in corporate-bond returns

Gebhardt, Hvidkjaer, and Swaminathan (2005) examine investment-grade bond returns from 1973 to 1996 and find no evidence of momentum. Their data are provided by Lehman Brothers and are month-end bid prices. Lehman's trading of these bonds and their use of these prices to construct their widely followed indices suggests that the data are accurate. Using the Lehman data, we extend the finding of no momentum in corporate-bond returns through 2004 and to high-yield bonds.

Each month t from 1990 to 2004 (the sample period for our bond funds), we rank bonds based on their returns over the prior 3, 6, and 12 months. We form equal-weighted portfolios with long positions in the top ten percent (winners) of the bonds and short positions in the bottom ten percent. These portfolios are examined over the following 3, 6, and 12 months using a calendar-time method. For example, to examine the 6-month holding-period performance, we average the returns of the 6 winner portfolios in calendar-month τ and the six loser portfolios. The winner-minus-loser return spread is then determined for month $\tau + 1$ using the 6 winner and 6 loser portfolios that are open in that month. The result is a calendar time-series of returns to winners minus losers over event months $[t + 1, t + 6]$.

We provide the profits to the winner-minus-loser portfolios from 1990 to 2004 for three combinations of ranking and holding periods: 3/3, 6/6, and 12/12. The other combinations are similar. We evaluate the performances of these portfolios using a two-factor model with the return to government bonds and the return spread between high-yield and high-quality bonds as the two factors.

	(W-L) Profits in Percent		
	3/3	6/6	12/12
High-quality	-0.20	-0.16	-0.26
	(-2.12)	(-2.07)	(-3.59)
High-yield	0.07	0.07	-0.03
	(1.01)	(0.98)	(-0.53)

There is no evidence of momentum in corporate-bond returns. If anything, returns display some reversal, consistent with the findings of Gebhardt, Hvidkjaer, and Swaminathan (2005). Skipping a month between ranking and holding periods, extending the data back to 1980, ranking based on factor-adjusted returns, and using only returns based on actual dealer quotes (instead of matrix prices) do not alter the findings.

It is useful to note that momentum in stock returns remains evident in the 1990 to 2004 period. The mean monthly return of Kenneth French's MOM factor is 0.893% per month with a t-statistic of 4.99.[14] The mean monthly return for MOM from 1963 to 1989 is 0.809% per month a with t-statistic of 3.43. Readers might also be interested in knowing that momentum exists in the stock returns of the firms in the bond sample, as Gebhardt, Hvidkjaer, and Swaminathan (2005) also find. From 1990 to 2004, we rank the stocks of the firms in our bond sample based on prior 6-month returns and form calendar-time portfolios to examine performance over a 6-month holding period. The mean alpha of the winners-minus-losers portfolio from the Fama and French (1993) model is 0.83% ($t = 2.19$) per month in the subsample of stocks with high-quality bonds and 2.31% ($t = 3.24$) per month in the subsample of stocks with high-yield bonds. The alphas over the 1980 to 2004 period, for which we have bond data, are similar.

[14] He provides the data on his website. MOM controls for size effects. In each month t, stocks are sorted into two portfolios based on size – B and S – and then each of these is sorted into three portfolios based on prior return over months $[t-12, t-2]$ – H, M, and L. MOM is the average return of the two H portfolios minus the average return of the two L portfolios.

A.2 Two-Index Model

Our "two-index" model uses the excess return of the Government/Corporate bond index (GC, labeled Aggregate index by Lehman, excludes high-yield bonds) and the excess return on the high-yield index over the one-month Treasury return as the benchmarks.

$$R_t = \alpha + \beta_1 GC_t + \beta_2 HY_t + \epsilon_t \tag{8}$$

A.3 Six-Factor Model

This model is based on Elton, Gruber, and Blake's (1995) six-factor model, where the six factors are:

- excess return on the CRSP value-weighted stock index (STK),
- excess return on the Lehman Aggregate bond index ($BOND$),
- return spread between the High-Yield index and the Intermediate Government index (DEF),
- return spread between the GNMA index and the Intermediate Government index ($OPTION$),
- change in the logarithm of the Composite Index of Leading Indicators (ILI)
- change in the logarithm of the Consumer Price Index (CPI, not seasonally adjusted, orthogonalized with respect to changes in ILI)

All fixed-income indices are again from Lehman Brothers. The data on the Composite Index of Leading Indicators is from Global Insight. The CPI data are from the Bureau of Labor and Statistics and are orthogonalized with respect to the index of leading indicators.[15]

To estimate the return premium (price of risk) of each of the non-traded macroeconomic factors, we form a maximum-correlation portfolio, first introduced by Breeden, Gibbons, and Litzenberger (1989). We regress (orthogonalized) changes in each of the two macroeconomic factors on the returns to a basis set of seventeen assets, which are

[15] Elton, Gruber, and Blake (1995) use survey data on forecasts of inflation and of GNP as two of their factors. We do not have access to such data so we replace these measures with changes in the CPI and changes in ILI respectively.

the Lehman Brothers Intermediate and Long indices for Aaa, Aa, A, Baa, Ba, B and Treasury bonds, the Intermediate Caa index, the 1-to-3-year Government index, and the Mortgage-Backed Securities index. The six-factor model then is

$$\begin{aligned} R_t &= \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_4 OPTION_t \\ &\quad + \beta_5 ILI_t^{MCP} + \beta_6 CPI_t^{MCP} + \epsilon_t \end{aligned} \tag{9}$$

where the superscript MCP indicates the use of the excess returns to the corresponding maximum-correlation portfolio. The mean excess return from 1990 to 2004 of the portfolio that tracks the ILI is -0.003% per month with a t-statistic of -0.24; the mean excess return of the portfolio that tracks the CPI is 0.05% per month with a t-statistic of 5.62. These premia estimates are sensitive to the method used. For example, a cross-sectional regression approach provides a mean premium of -0.51% for ILI and a mean premium of 0.10% for CPI. We do not employ the cross-sectional-regression estimates in our testing.

A.4 Market-Timing Models

We examine the possiblity that the managers of corporate-bond funds can "time" the market. The general notion is that a fund manager will increase the fund's sensitivity to a certain factor when the manager forecasts that factor to realize a higher return and will decrease the sensitivity when the forecast is a lower return. We employ two standard models of market timing, one by Treynor and Mazuy (1966) and the other by Henriksson and Merton (1981). The two-factor and style models in section 2 as well as the six-factor model above are extended to include a timing parameter as follows. In the Treynor-Mazuy case,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k F_{kt}^2 + \epsilon_t \tag{10}$$

where γ_k is the market-timing parameter for factor k which captures the variation in the fund's β_k as a function of the factor premium. In the Henriksson-Merton case,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k \max(0, F_{kt}) + \epsilon_t \tag{11}$$

where γ_k is again the market-timing parameter. In these specifications, we examine the possibility that fund managers can time any or all of the factors.[16]

A.5 Conditional Models

Keim and Stambaugh (1986), Fama and French (1989), and others provide evidence that bond returns predictably change through time. If expected returns vary, the unconditional performance metrics described above can be flawed. To accomodate potential time variation in the risks of a fund's underlying assets as well as the potential for a fund manager to dynamically respond to time variations in expected returns, we follow the approach of Ferson and Schadt (1996) and assume that conditional factor loadings are a linear function of a vector of lagged, predetermined economic variables Z_{t-1}. Specifically, equation (1) becomes

$$R_t = \alpha + \sum_k \beta_{kt} F_{kt} + \epsilon_t \tag{12}$$

where

$$\beta_{kt} = b_k^1 + b_k^2 Z_{t-1}. \tag{13}$$

The coefficient b_k^1 is the unconditional mean of the conditional beta β_{kt}, and b_k^2 captures the sensitivity of the conditional beta to changes in Z_{t-1}. We adapt the two-factor and style models from section 2 as follows.

$$R_t = \alpha + \sum_k b_k^1 F_{kt} + \sum_k b_k^2 \left(F_{kt} \otimes Z_{t-1}\right) + \epsilon_t. \tag{14}$$

[16] Jagannathan and Korajczyck (1986), Glosten and Jagannathan (1994), Ferson and Schadt (1996), and Edelen (1999) identify potential concerns of such tests of market timing.

The conditioning variables Z_{t-1} are the level and the slope of the term structure and the default spread in the corporate-bond market. The data for these variables are from the Federal Reserve System. The level is captured by the yield of the 3-month Treasury bill. The slope is captured by the yield of the 10-year Treasury Constant Maturity over the yield of the 1-year Treasury Constant Maturity. The default spread is captured by the yield of Baa corporate bonds over the yield of Aaa corporate bonds. We use sixty-month lagged moving averages of each of these conditioning variables to reduce the problem of spurious regressions which can be a result of using such persistent variables, as suggested by Ferson, Sarkissian, and Simin (2003).

A.6 Stale pricing

Corporate bonds are known to be relatively illiquid assets that can trade infrequently. One potential consequence of illiquidity is that bond prices can be stale and not fully updating of current information. Stale pricing can lead to misestimation of a fund's factor risks and consequently to misestimation of performance.

To adjust for any stale bond prices in the reported fund returns, we add one lagged term corresponding to each factor in the two-factor model and the style model respectively. We also include one lead term for each factor to accommodate the possibility that some funds might be updating bond prices ahead of the Lehman indices.[17] We find that the fund returns generally do not load on the lagged and leading factors.

This method only considers stale pricing in the systematic components of returns however. Addressing bond-specific stale pricing is a difficult task. We observe in section 6.3 that serial correlation in factor-adjusted fund returns is low, suggesting that idiosyncratic stale pricing does not have a material effect on our analyses.[18]

[17]The Lehman indices are formed from bid quotes determined by Lehman's analysts. These quotes are updated monthly and provide some assurance that Lehman's prices are not stale. Moreover, the indices are value-weighted. To the extent that staleness is less likely in large bonds, we have further assurance.

[18]Stale pricing can also lead (passively or actively) to the smoothing of fund returns. Getmansky, Lo, and Makarov (2004) provide an excellent discussion of illiquidity, stale pricing, and return smoothing in the context of hedge funds. We have more to say on these issues in section 6.3.

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Table 1. Summary Statistics of Annual Returns

Panels A and B report various statistics for annual returns of high-quality and high-yield corporate bond funds, respectively, over three subperiods (1990-1994, 1995-1999 and 2000-2004) as well as the full period (All). Panel C provides statistics over the full period for the annual returns of the benchmark portfolios (factors) we use to evaluate fund performance. We require funds to have at least 24 months of returns (for reasonable estimation of factor loadings in subsequent tests).

	N	MeanRet(%)	MedianRet(%)	StdDev	Skewness	Kurtosis
Panel A : High-Quality Bond Funds						
1990 – 1994	1572	6.42	6.16	6.19	-0.25	1.65
1995 – 1999	3839	6.04	6.13	5.20	0.37	0.71
2000 – 2004	5492	5.57	6.34	1.83	-0.51	-1.38
All	10903	6.01	6.16	4.45	0.15	0.86
Panel B : High-Yield Bond Funds						
1990 – 1994	478	9.09	14.42	16.44	0.00	-1.27
1995 – 1999	1101	8.28	11.52	6.28	-0.78	-1.54
2000 – 2004	2009	4.22	1.86	10.65	0.56	0.08
All	3588	7.20	9.06	11.22	0.22	-0.21
Panel C : Factors						
Aggregate		7.35	8.39	5.41	-0.20	-0.02
Government		7.31	8.34	5.85	-0.36	-0.37
High-Quality		8.16	8.46	6.16	-0.11	0.84
High-Yield		9.38	10.67	12.55	0.78	0.91
Default		2.61	4.14	12.35	0.16	0.13
Option		0.61	0.60	1.21	-0.56	-0.65
Stock		7.35	11.44	17.03	-0.51	-1.18

Table 2. Characteristics of Corporate-Bond Funds

Over three subperiods and the full period (All), the respective means of various fund characteristics and percentage holdings in certain asset classes are given for our sample of high-quality and high-yield corporate-bond funds, in Panels A and B respectively. Age is the length of time in years between the first offered date and the last available monthly return in the given sample period. TNA is total net assets under management, reported in millions. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average total net assets of the fund. Load is the sum of all maximum front, deferred and redemption fees as a percentage of the fund's total net assets. Expense ratios are from fiscal year-ends and are a percentage of assets. The right side of the table gives the mean percentages of fund investment in corporate bonds, government bonds, municipal bonds, convertible bonds, common stocks, preferred stocks, and other securities. For each of the reported measures, we first average across funds and then average across years.

	Age	TNA	Turn-over	Load	Exp. Ratio	Corp. Bonds	Govt. Bonds	Muni. Bonds	Conv. Bonds	Com. Stocks	Pref. Stocks	Cash	Other
Panel A : High-Quality Funds													
1990–1994	5.94	190.10	1.32	1.77	0.87	40.80	38.14	1.29	0.73	0.44	0.27	9.79	6.02
1995–1999	5.50	211.81	1.70	1.49	0.95	41.64	38.45	0.62	0.77	0.42	0.40	6.67	9.87
2000–2004	7.01	307.19	1.72	1.59	1.00	50.05	32.99	0.91	0.15	0.38	0.33	6.62	5.94
All	6.33	256.48	1.67	1.58	0.96	45.94	35.56	0.85	0.44	0.40	0.35	7.01	7.36
Panel B : High-Yield Bond Funds													
1990–1994	9.06	350.73	0.90	3.48	1.31	83.22	2.05	1.40	0.79	1.73	2.09	5.93	2.00
1995–1999	6.16	370.15	1.10	2.72	1.35	84.22	1.66	0.01	1.66	1.44	3.32	4.98	1.53
2000–2004	6.93	257.72	1.02	2.38	1.32	84.01	2.80	0.01	0.98	1.39	2.44	4.98	1.79
All	6.97	304.74	1.03	2.63	1.33	84.01	2.36	0.14	1.18	1.44	2.69	5.06	1.73

Table 3. Performance of Net Returns

For funds with at least 24 months of returns, we estimate the mean monthly risk-adjusted performance (α) of each fund over its available months using the two-factor, four-factor, and style models from section 2. Analysis is at the share-class level. Panel A gives various statistics for the cross section of α for high-quality and high-yield funds respectively, as well as the adjusted R^2 from the factor-model regressions. We also report the performance of the equally weighted portfolio (α_{EW}) of all available funds each month over the sample period 1990 to 2004. Panel B provides the Spearman rank correlations between the performance measures.

Panel A: Risk Adjusted Performance

	High-Quality Funds			High-Yield Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
Mean α	-0.02	-0.06	-0.06	-0.03	-0.07	-0.02
Median α	-0.02	-0.05	-0.05	-0.01	-0.04	0.00
Std dev of α	0.10	0.10	0.11	0.27	0.27	0.26
Fraction with $\alpha > 0$ (5% level)	0.10	0.05	0.04	0.09	0.07	0.12
Fraction with $\alpha < 0$ (5% level)	0.18	0.41	0.40	0.13	0.16	0.12
Mean t-statistic	-0.34	-1.57	-1.59	-0.08	-0.40	0.02
Mean Adj R^2	0.79	0.85	0.86	0.78	0.83	0.84
α^{EW}	-0.03	-0.05	-0.05	-0.04	-0.03	-0.01
t-stat	(-1.29)	(-5.84)	(-4.69)	(-0.69)	(-0.70)	(-0.39)

Panel B: Spearman Rank Correlation

	High-Quality Funds			High-Yield Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
2-Factor	1.00			1.00		
4-factor	0.85	1.00		0.95	1.00	
Style	0.82	0.83	1.00	0.87	0.86	1.00

Table 4. Performance of Gross Returns

For funds with at least 24 months of returns, we estimate the mean monthly risk-adjusted performance gross of expenses (α) for each fund over its available months using the two-factor, four-factor, and style models from section 2. Analysis is at the fund level, not the share-class level. Panel A gives various statistics for the cross section of α for high-quality and high-yield funds respectively, as well as the adjusted R^2 from the factor-model regressions. We also report the performance of the equally weighted portfolio (α_{EW}) of all available funds each month over the sample period 1990 to 2004. Panel B provides the Spearman rank correlations between the performance measures.

Panel A: Risk-Adjusted Performance

	High-Quality Funds			High-Yield Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
Mean α	0.05	0.01	0.02	0.07	0.04	0.09
Median α	0.06	0.02	0.02	0.10	0.07	0.10
Std dev of α	0.10	0.10	0.11	0.26	0.24	0.23
Fraction with $\alpha > 0$ (5% level)	0.40	0.26	0.22	0.24	0.21	0.31
Fraction with $\alpha < 0$ (5% level)	0.02	0.05	0.04	0.05	0.05	0.03
Mean t-statistic	1.60	0.87	0.84	0.85	0.70	1.04
Mean Adj R^2	0.79	0.84	0.86	0.76	0.81	0.82
α^{EW}	0.05	0.03	0.03	0.08	0.07	0.06
t-stat	(2.66)	(2.98)	(2.61)	(1.38)	(1.66)	(1.50)

Panel B: Spearman Rank Correlation

	High-Quality Funds			High-Yield Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
2-Factor	1.00			1.00		
4-factor	0.81	1.00		0.94	1.00	
Style	0.80	0.79	1.00	0.87	0.87	1.00

Table 5. Persistence in Performance of High-Quality Funds

Each month starting in January 1992, we rank high-quality corporate-bond funds into deciles based on their lagged 12-month performances, using factor loadings estimated over the prior 24 months. Panel A ranks funds based on the two-factor model, Panel B on the four-factor model, and Panel C on the style model. We then estimate the future performance of the equally weighted top decile of funds (Winner), the bottom decile (Loser), and the difference between the two (W−L). On the left side of the table, ranking and future performance is based on net returns and is at the share-class level. On the right side, ranking and future performance is based on gross returns (before expenses) and is at the fund level. Future performance is determined using a calendar-time procedure over two holding periods, 1 month and 48 months, based on the two-factor, four-factor, and style models. The *t*-statistics are in parentheses.

	Net Returns			Gross Returns		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
Panel A: Ranking with 2-Factor Model						
Holding Period: 1 month						
Winner	0.04	0.01	0.01	0.12	0.08	0.08
	(1.34)	(0.39)	(0.24)	(3.65)	(3.54)	(3.23)
Loser	-0.13	-0.17	-0.15	-0.04	-0.07	-0.05
	(-3.50)	(-6.36)	(-5.84)	(-1.02)	(-2.74)	(-1.93)
W-L	0.18	0.18	0.15	0.16	0.16	0.13
	(4.61)	(4.75)	(4.24)	(3.95)	(3.99)	(3.46)
Holding Period: 48 month						
Winner	0.02	-0.02	-0.01	0.08	0.04	0.05
	(0.59)	(-1.12)	(-0.70)	(2.55)	(2.42)	(2.82)
Loser	-0.08	-0.11	-0.10	0.03	0.00	0.00
	(-2.71)	(-6.52)	(-5.71)	(1.00)	(-0.14)	(0.27)
W-L	0.10	0.10	0.09	0.05	0.04	0.05
	(4.87)	(4.81)	(4.42)	(2.27)	(2.09)	(2.09)

Panel B: Ranking with 4-Factor Model						
Holding Period: 1 month						
Winner	0.07	0.04	0.03	0.12	0.09	0.09
	(2.36)	(1.79)	(1.42)	(3.92)	(3.83)	(3.51)
Loser	-0.13	-0.17	-0.14	-0.03	-0.07	-0.04
	(-3.41)	(-6.65)	(-6.11)	(-0.83)	(-2.78)	(-1.90)
W-L	0.20	0.21	0.18	0.15	0.16	0.13
	(5.47)	(5.85)	(5.30)	(4.11)	(4.27)	(3.78)
Holding Period: 48 month						
Winner	0.02	-0.01	-0.01	0.08	0.05	0.05
	(0.82)	(-0.79)	(-0.68)	(2.84)	(2.77)	(2.75)
Loser	-0.08	-0.12	-0.10	0.03	-0.01	0.00
	(-2.65)	(-6.61)	(-5.66)	(0.85)	(-0.45)	(0.18)
W-L	0.10	0.11	0.09	0.05	0.05	0.05
	(5.01)	(5.31)	(4.61)	(2.62)	(2.62)	(2.22)

Panel C: Ranking with Style Model						
Holding Period: 1 month						
Winner	0.07	0.05	0.04	0.14	0.11	0.12
	(2.65)	(2.51)	(2.06)	(5.07)	(6.06)	(5.65)
Loser	-0.13	-0.17	-0.16	-0.02	-0.06	-0.05
	(-3.69)	(-7.98)	(-8.09)	(-0.67)	(-2.87)	(-2.54)
W-L	0.20	0.21	0.20	0.17	0.17	0.17
	(8.38)	(9.52)	(9.07)	(7.22)	(7.78)	(7.50)
Holding Period: 48 month						
Winner	0.03	0.00	0.00	0.09	0.06	0.06
	(1.05)	(0.04)	(-0.07)	(3.21)	(3.58)	(3.40)
Loser	-0.09	-0.12	-0.11	0.03	-0.01	0.00
	(-2.95)	(-8.34)	(-7.62)	(1.00)	(-0.40)	(0.03)
W-L	0.12	0.12	0.11	0.06	0.06	0.06
	(7.96)	(8.54)	(7.96)	(4.74)	(4.83)	(4.36)

Table 6. Persistence in Performance of High-Yield Funds

Each month starting in January 1992, we rank high-yield corporate-bond funds into deciles based on their lagged 12-month performances, using factor loadings estimated over the prior 24 months. Panel A ranks funds based on the two-factor model, Panel B on the four-factor model, and Panel C on the style model. We then estimate the future performance of the equally weighted top decile of funds (Winner), the bottom decile (Loser), and the difference between the two (W−L). On the left side of the table, ranking and future performance is based on net returns and is at the share-class level. On the right side, ranking and future performance is based on gross returns (before expenses) and is at the fund level. Future performance is determined using a calendar-time procedure over two holding periods, 1 month and 48 months, based on the two-factor, four-factor, and style models. The t-statistics are in parentheses.

	Net Returns			Gross Returns		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
	Panel A: Ranking with 2-Factor Model					
Holding Period: 1 month						
Winner	0.17	0.17	0.18	0.28	0.27	0.29
	(2.49)	(2.77)	(2.90)	(3.84)	(4.30)	(4.57)
Loser	-0.43	-0.42	-0.36	-0.29	-0.27	-0.21
	(-5.39)	(-5.86)	(-5.13)	(-3.75)	(-3.82)	(-3.17)
W-L	0.60	0.59	0.54	0.56	0.54	0.51
	(7.94)	(7.73)	(6.97)	(8.18)	(7.72)	(7.22)
Holding Period: 48 month						
Winner	0.01	0.02	0.04	0.11	0.12	0.14
	(0.23)	(0.46)	(0.86)	(1.73)	(2.18)	(2.76)
Loser	-0.23	-0.23	-0.18	-0.10	-0.09	-0.04
	(-3.49)	(-4.03)	(-3.20)	(-1.56)	(-1.68)	(-0.83)
W-L	0.25	0.26	0.22	0.20	0.21	0.18
	(5.02)	(5.16)	(4.30)	(5.01)	(5.05)	(4.33)

Panel B: Ranking with 4-Factor Model						
Holding Period: 1 month						
Winner	0.15	0.15	0.17	0.26	0.26	0.27
	(2.23)	(2.53)	(2.89)	(3.60)	(4.10)	(4.44)
Loser	-0.39	-0.38	-0.32	-0.30	-0.29	-0.21
	(-4.81)	(-5.38)	(-4.55)	(-3.68)	(-3.79)	(-2.98)
W-L	0.54	0.53	0.48	0.56	0.55	0.48
	(7.58)	(7.41)	(6.62)	(7.54)	(7.19)	(6.53)
Holding Period: 48 month						
Winner	0.01	0.02	0.05	0.11	0.11	0.15
	(0.16)	(0.35)	(0.96)	(1.68)	(2.09)	(2.90)
Loser	-0.19	-0.19	-0.14	-0.06	-0.06	-0.01
	(-3.00)	(-3.63)	(-2.72)	(-1.03)	(-1.24)	(-0.18)
W-L	0.20	0.21	0.19	0.17	0.18	0.16
	(5.17)	(5.41)	(4.61)	(4.38)	(4.59)	(3.87)

Panel C: Ranking with Style Model						
Holding Period: 1 month						
Winner	0.11	0.10	0.12	0.20	0.18	0.25
	(1.55)	(1.65)	(2.51)	(2.60)	(2.80)	(3.89)
Loser	-0.35	-0.33	-0.31	-0.23	-0.19	-0.16
	(-5.00)	(-4.98)	(-4.92)	(-3.05)	(-2.79)	(-2.46)
W-L	0.46	0.42	0.46	0.43	0.38	0.41
	(6.93)	(6.33)	(6.50)	(5.55)	(4.90)	(5.18)
Holding Period: 48 month						
Winner	0.00	0.00	0.03	0.09	0.09	0.12
	(0.02)	(0.06)	(0.68)	(1.38)	(1.72)	(2.51)
Loser	-0.18	-0.16	-0.13	-0.05	-0.03	0.00
	(-2.97)	(-2.89)	(-2.66)	(-0.86)	(-0.53)	(-0.04)
W-L	0.18	0.16	0.16	0.14	0.12	0.13
	(5.79)	(5.15)	(5.07)	(4.24)	(3.55)	(3.76)

Table 7. Characteristics of Decile Portfolios Ranked on Prior 12-Month Performance

Each month t we rank funds at the share-class level based on net performance over the prior 12 months using the two-factor model, with factor loadings estimated over the prior 24 months. The means of various characteristics are calculated across funds within each decile and then averaged over time. Load is the sum of all maximum front, deferred and redemption fees as a percentage of the fund's total net assets. Age is the length of time in years between the first offered date and month t. TNA is total net assets under management, reported in millions and then logged. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average total net assets of the fund. Expense ratios are a percentage of assets. Load and TNA are from month t. Turnover and expense ratios are from month $t+1$. The raw return, two-factor performance (α), and the t-statistic for two-factor performance are for month $t+1$. Panels A and B present the results for high-quality and high-yield corporate-bond funds, respectively.

Decile	Load	Age (Years)	TNA (logs)	Exp. Ratio	Turn-over	Raw Return	α	t stat
			Panel A : High-Quality Bond Funds					
1-Winner	1.24	8.84	4.72	0.07	2.06	0.58	0.04	(1.30)
2	1.19	9.49	4.71	0.06	1.61	0.52	0.02	(0.76)
3	1.26	9.01	4.59	0.06	1.78	0.51	0.01	(0.33)
4	1.35	8.52	4.45	0.07	1.58	0.51	0.00	(0.00)
5	1.47	8.42	4.32	0.07	1.67	0.49	-0.01	(-0.73)
6	1.60	8.15	4.12	0.07	1.46	0.48	-0.03	(-1.38)
7	1.80	8.35	3.99	0.08	1.38	0.48	-0.04	(-1.67)
8	1.87	8.18	3.83	0.09	1.44	0.48	-0.04	(-1.59)
9	2.15	8.35	3.64	0.09	1.49	0.47	-0.06	(-2.47)
10-Loser	2.39	9.04	3.55	0.10	1.59	0.44	-0.13	(-3.33)
			Panel B : High-Yield Bond Funds					
1-Winner	2.60	10.71	4.97	0.10	1.16	0.81	0.17	(2.52)
2	3.06	10.56	4.94	0.10	1.08	0.72	0.07	(1.28)
3	3.18	10.33	4.98	0.10	1.04	0.70	0.05	(0.81)
4	3.26	9.97	4.98	0.10	0.99	0.64	-0.02	(-0.45)
5	3.31	10.21	5.05	0.11	0.93	0.64	-0.02	(-0.42)
6	3.20	10.08	5.05	0.10	0.92	0.61	-0.05	(-0.95)
7	3.18	9.80	5.01	0.11	0.87	0.59	-0.08	(-1.63)
8	3.17	9.44	5.02	0.11	0.95	0.56	-0.13	(-2.17)
9	3.21	9.09	4.88	0.12	1.00	0.49	-0.20	(-3.11)
10-Loser	3.08	9.72	4.46	0.12	1.15	0.29	-0.41	(-5.19)

Table 8. Future Fund Performance and Fund Characteristics

Each month starting in January 1992, we examine whether prior fund net performance (over the prior 12 months and prior 48 months respectively) predicts next year's net performance. Analysis is at the share-class level. We employ a calendar-time, cross-sectional method described in section 6.2. $\alpha_{[t-12,t-1]}$ is risk-adjusted return over months $[t-12,t-1]$), and $\alpha_{[t-48,t-1]}$ over months $[t-48,t-1]$). LoadDum is equal to one if a fund has a load, and 0 otherwise. Age is the time between the first offered date and a given month. TNA is total net assets under management, reported in millions. Expenses are a percentage of assets. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities, divided by the average total net assets of the fund. Performance is evaluated using either the two-factor or style models. For the dependent variable and the prior one-year alpha, we use factor loadings estimated over the prior 24 months. The t-statistics are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

Dep. Var.	2-Factor Alphas			Style Alphas	
	$\alpha_{[t,t+11]}$	$\alpha_{[t,t+11]}$		$\alpha_{[t,t+11]}$	$\alpha_{[t,t+11]}$
Panel A: High-Quality Funds					
$\alpha_{[t-12,t-1]}$	0.15			0.24	
	(3.66)			(6.54)	
$\alpha_{[t-48,t-1]}$		0.28			0.37
		(3.95)			6.07)
LoadDum	-0.01	0.00		-0.01	-0.01
	(-2.53)	(-0.56)		(-3.02)	(-0.87)
Age	0.00	0.00		0.00	0.00
	(0.63)	(0.37)		(-1.88)	(-0.83)
log(TNA)	0.01	0.01		0.00	0.00
	(2.53)	(2.67)		(3.79)	(2.32)
Expense	-0.51	-0.44		-0.69	-0.68
	(-3.07)	(-2.12)		(-10.84)	(-7.56)
Turnover	0.00	0.00		0.00	0.00
	(0.74)	(-0.46)		(0.63)	(0.33)
Adj R^2	0.24	0.26		0.17	0.17
Panel B: High-Yield Funds					
$\alpha_{[t-12,t-1]}$	0.24			0.27	
	(4.94)			(3.97)	
$\alpha_{[t-48,t-1]}$		0.57			0.61
		(4.09)			(3.32)
Loaddum	-0.03	-0.02		-0.02	-0.02
	(-1.43)	(-0.78)		(-0.84)	(-1.01)
Age	0.00	0.00		0.00	0.00
	(0.83)	(0.43)		(1.83)	(0.68)
log(TNA)	0.00	0.01		0.00	0.00
	(0.02)	(0.68)		(-0.76)	(0.12)
Expense	-0.37	-0.23		-0.40	-0.20
	(-2.02)	(-0.97)		(-2.66)	(-1.07)
Turnover	0.00	-0.02		0.00	-0.04
	(0.21)	(-0.45)		(-0.34)	(-1.26)
Adj R^2	0.31	0.31		0.23	0.22

Table 9. Regressions of Net Flow on Prior 12-Month Performance

Each month starting January 1992, we regress the cross section of net flow in month t (as a percentage of total net assets) on prior performance and other fund characteristics. We begin by ranking funds based on their two-factor alphas over months $[t-12, t-1]$, assigning a percentile rank to each fund ($rank$). The factor loadings used to calculate the alphas are estimated over the prior 24 months. Following Sirri and Tufano (1998), we estimate the following linear regression piecewise over quintiles of lagged performance. Specifically, we define five variables (Q1 to Q5) based on percentile ranking of prior performance. For $i = 1$ to 5, $\mathrm{Q}i = \begin{cases} 0 & \text{if } rank < \frac{i-1}{5} \\ \min\left(rank - \frac{i-1}{5}, 0.20\right) & \text{if } rank \geq \frac{i-1}{5} \end{cases}$ The coefficients on these variables capture the sensitivity of flow to prior performance within quintiles 1 to 5 respectively. The characteristics sampled at month $t-1$ are monthly 12b-1 fees, monthly expenses less 12b-1 fees, load dummy, log(TNA), and flow over the past 12 months. We delete the top and the bottom 2.5% of the flow observations. The t-statistics are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

	High-Quality Funds	High-Yield Funds
12b1 fee	0.01	0.01
	(0.31)	(0.51)
Expenses (less 12b1 fee)	-0.04	-0.03
	(-3.01)	(-1.36)
LoadDum	0.00	0.00
	(-0.87)	(0.41)
log(TNA)	0.00	0.00
	(-5.81)	(-7.83)
$\mathrm{Flow}_{[t-12,t-1]}$	0.04	0.04
	(15.79)	(12.24)
Q1 (Lowest)	0.02	0.05
	(2.46)	(4.57)
Q2	0.01	0.01
	(2.00)	(1.64)
Q3	0.01	0.00
	(2.23)	(0.04)
Q4	0.00	0.01
	(0.17)	(2.11)
Q5 (Highest)	0.03	0.04
	(3.89)	(3.23)
Adj R^2	0.23	0.41

Table 10. Portfolio Tests of Smart Money

Each month t we identify funds with net inflows and net outflows over the prior three months. We form a portfolio of funds with positive net flow (Inflow) and another portfolio of funds with negative net flow (Outflow). Both equal-weighted and flow-weighted portfolios are examined. These portfolios are held for either three or twelve months and their risk-adjusted performances, as well their differences in performance (I−O), are estimated with the 2-factor model or the style model using a calendar-time procedure. The t-statistics are in parentheses.

	Equal-Weighted Portfolios				Flow-Weighted Portfolios			
	2-Factor		Style		2-Factor		Style	
Panel A: High-Quality Funds								
Holding Period: 3 month								
Inflow	0.005	(0.16)	-0.019	(-0.63)	0.022	(0.93)	-0.003	(-0.15)
Outflow	-0.020	(-0.98)	-0.043	(-3.54)	0.004	(0.16)	-0.014	(-0.85)
I−O	0.025	(0.92)	0.024	(0.85)	0.019	(1.10)	0.011	(0.63)
Holding Period: 12 month								
Inflow	-0.010	(-0.40)	-0.035	(-1.95)	0.030	(1.07)	0.003	(0.11)
Outflow	-0.014	(-0.68)	-0.039	(-3.30)	0.008	(0.39)	-0.016	(-1.12)
I−O	0.004	(0.36)	0.004	(0.35)	0.021	(1.17)	0.019	(0.99)
Panel B: High-Yield Funds								
Holding Period: 3 month								
Inflow	-0.022	(-0.44)	-0.011	(-0.28)	-0.020	(-0.37)	-0.005	(-0.11)
Outflow	-0.098	(-1.90)	-0.078	(-2.18)	-0.089	(-1.50)	-0.068	(-1.50)
I−O	0.075	(4.62)	0.067	(4.07)	0.069	(2.76)	0.063	(2.55)
Holding Period: 12 month								
Inflow	-0.036	(-0.68)	-0.021	(-0.55)	-0.057	(-1.02)	-0.037	(-0.89)
Outflow	-0.089	(-1.75)	-0.070	(-1.96)	-0.088	(-1.56)	-0.068	(-1.63)
I−O	0.053	(4.40)	0.049	(3.99)	0.031	(1.78)	0.032	(1.82)

Table 11. Regression Tests of Smart Money

Each month t we regress the cross section of future performance on prior performance and other fund characteristics. We essentially use the same procedure as in Table 8, but we include dollar flow in a given fund over $[t-1, t-3]$ as an additional explanatory variable, to examine the effect of flow in the presence of prior performance . We also examine future performance over $[t, t+2]$ in addition to performance over $[t+1, t+12]$. Prior performance is measured over three horizons, $[t-3, t-1]$, $[t-12, t-4]$, and $[t-24, t-13]$. Both prior and future performance are estimated using the two-factor model. All alphas are calculated using factor loadings estimated over 24 months. The t-statistics are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

	$\alpha_{[t,t+2]}$	$\alpha_{[t,t+11]}$	$\alpha_{[t,t+2]}$	$\alpha_{[t,t+11]}$
	High-Quality Funds		High-Yield Funds	
$\text{Flow}_{[t-3,t-1]}$	0.000	0.000	0.000	0.000
	(0.101)	(-0.409)	(-0.434)	(-0.460)
$\alpha_{[t-3,t-1]}$	0.054	0.065	0.240	0.154
	(1.559)	(4.185)	(6.394)	(5.103)
$\alpha_{[t-12,t-4]}$	0.125	0.052	0.197	0.105
	(2.431)	(1.151)	(2.646)	(2.198)
$\alpha_{[t-24,t-13]}$	-0.014	0.034	-0.074	0.024
	(-0.309)	(0.746)	(-1.187)	(0.350)
LoadDum	-0.008	-0.011	-0.017	-0.024
	(-2.108)	(-2.217)	(-0.828)	(-1.074)
Age	0.000	0.000	0.001	0.000
	(0.232)	(0.068)	(0.819)	(0.069)
log(TNA)	0.004	0.006	0.000	0.004
	(2.182)	(2.822)	(0.033)	(0.491)
Expense	-0.629	-0.521	-0.302	-0.302
	(-3.972)	(-3.115)	(-1.399)	(-1.327)
Turnover	0.002	0.002	0.007	0.010
	(1.348)	(1.809)	(0.423)	(0.538)
Adj R^2	0.323	0.316	0.416	0.379