Persistent Performance in Corporate-Bond Mutual Funds

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Abstract

We provide a comprehensive evaluation of 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. We also find that the top decile of funds over the past year outperform the bottom decile, net of expenses and trading costs, by ten basis points per month over the next four years. This spread is twenty basis points per month for high-yield funds. The persistent performance between winners and losers that we detect is not due to expenses or trading costs and is driven largely by the loser funds continuing to lose. However, we do find evidence of the winners' continuing to win for a few months. Moreover, we find that winners are able to generate positive alpha gross of expenses over the next four years, evidencing their skill in trading bonds. Investors do not realize this performance though as the winners' net returns are not abnormal, consistent with a competitive equilibrium. We then examine if investors are able to exploit the persistence in performance and find that flows to these funds depend on prior performance and that, for high-yield funds, funds with inflows outperform funds with outflows over the next year. In sum, our findings suggest that some fund managers have an ability to identify misvaluations in the bond market, that variation in skill across managers can be detected using prior performance, and that managers face more rapidly diminishing returns to scale in the high-quality bond market than in the high-yield market. 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 performances of equity funds is largely due to momentum in the underlying stock returns. This link between persistence in fund performance and stock 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 effects in returns despite two of their factors being based on size and book-to-market 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 fees, abnormal returns of high-quality-bond funds fall to around -5 basis points per month. The average performance of funds trading high-yield bonds however is statistically zero, both before and after fees. 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 peformance is long lasting, due seemingly to fees and trading costs. As a consequence, there is a persistent spread between the performances of the prior winners and the prior losers that averages 10 to 15 basis points per month over four years for high-quality funds and from 13 to 25 basis points for high-yield funds, depending on the performance metric and the ranking horizon. This persistent spread is not due to expenses or trading costs since winners and losers do not appear to differ along these dimensions. Instead, the persistent spread seems due to the skill of the winning fund managers. Before fees, last year's high-quality winner funds beat the market by 5 basis points per month over the next four years; last year's high-yield winner funds beat the market by 10 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 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 perfromance 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 benefitting 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 smart money in the net flows of bond funds. 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 accomodate 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. Our main conclusions are unaltered by the use of the other models, which are described in the Appendix. We now detail the three models that will guide us through the paper.

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 identifiying 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 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 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.)[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

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

[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.

level, but examining at the fund level (with asset-weighted returns) produces similar findings. For returns gross of performance, we examine 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 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 return properties for high-quality funds is relatively stable across the sample period, whereas the average, minimum, maximum, and standard deviation of returns 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 Goverment indexes deviate little from each other across the return given properties, 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 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, such as 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 high-yield funds. The remaining bond and stock categories receive little weight. In fact, cash is the next largest category for 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

Since prior studies of corporate-bond funds are limited and dated in their samples, we provide in this section a detailed examination of the average performances of these bond funds, before addressing persistence in their performance and "smart" money.

4.1 Net of expenses

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).

To make the tables manageable, we tabulate performances based on the two-factor, the style model, and the four-factor model. The six-factor model as well as the conditional, the market-timing, and the stale-pricing variants of the base models (which are all described in the Appendix) typically lead to similar findings and do not alter any overall conclusions.

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 -0.06% 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 -0.02%, but no estimate is significantly negative.[7]

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.

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.[8] The set of evidence, including the untabulated models, suggests that HY fund managers might be better able to offset the expenses charged to 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

[7]Four of the untabulated models produce point estimates of alpha that are greater than zero and insignificant. These are market-timing models. However, only the timing parameter on the DEF factor in the six-factor model is significantly different from zero, and negative, for both the Treynor-Mazuy and Henriksson-Merton models. Of all timing parameters across the models, about half of the point estimates are negative for the EW portfolio of HY funds.

[8]The untabulated models find greater dispersion in the estimates of the alpha of the EW portfolio of HY funds (varying from -0.16 to 0.08), with two significantly negative.

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 base models, ranging from 0.01% to 0.05% per month. The gross alphas for the EW portfolio of HQ funds range from 0.02% 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 for the base models 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.[9] 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. High-quality fund managers though seem able to identify and invest in corporate bonds that produce mildly positive alphas on average.

[9]The filtered sample where 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 are removed produces more evidence of positive alpha in the three base models, and roughly half of the untabulated models provide evidence of positive alpha in the EW portfolio of HY funds. Interestingly, the market-timing specifications provide the bulk of the evidence for positive alpha. While the alphas are on average greater using these market-timing models, the evidence of market timing however is weak. Of the thirty-two timing parameters estimated across eight models, twenty-five are negative, with five having t-statistics less than -2.0. And for HQ funds, the timing parameters are significant with even less frequency, with the mix between negative and positive point estimates getting much closer. For comparison, equity mutual funds display, if anything, this same tendency toward perverse, 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.

5 Persistence in Performance

We now consider whether the best corporate-bond funds in the past continue to be 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 the three base 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 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 that the evidence of positive alpha remains in some metrics for up to twelve months, dissipating thereafter. 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 continue to beat their benchmarks for a brief horizon, spanning under two years across ranking and holding periods. In contrast, the HQ losers, regardless of ranking horizon, continue to lose sizably over the next four years.

5.1.2 Gross returns

Turning to persistence in gross returns, we see on the right side of Table 5 that 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. For longer horizons though, no model finds evidence of losers' gross returns producing negative alphas for any prolonged period.

5.2 Robustness: Aggregation of Loadings

Before we examine the persistence in the performance of HY funds, we wish to note an additional robustness check on the holding-period performance of the portfolios. Since the composition of the portfolios is changing each month as the new winner and loser funds enter the portfolio and the oldest winner and loser funds exit, our assumption that the factor loadings are constant over the entire time series of post-ranking months examined might be flawed. We use the estimated loadings of the individual funds that comprise the respective winner and loser portfolios to estimate the loadings of the winner and loser portfolios each month. In calendar month τ, for the winner portfolio and for the loser portfolio respectively, we estimate the component funds' loadings over $[\tau, \tau + 23]$ and average these loadings to obtain an estimate of the corresponding portfolio's loadings. We then estimate the portfolios' loadings in the next calendar month, and so on. We do not tabulate these results because the general conclusions are the same as those using the constant-loading specifications for the HQ and the HY funds.

5.3 High-yield funds

5.3.1 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% per month, 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 indicate that any evidence of positive alpha for the 12-month winners is gone by month 12 of the holding period. In short, persistence in the good performance of winner funds is more evident in HY funds, but such persistence is 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.

5.3.2 Gross returns

Turning to the gross performance of HY funds, we see on the right side of Table 6 that HY managers continue to beat the market 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, with only one t-statistic less than 1.65. Again we have the noteworthy finding 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%. Untabulated results indicate that this negative performance continues for at least one year. This persistence in poor performance when using returns gross of expenses seems perplexing at first, since we do not expect managers to consistently err by picking negative-alpha bonds. We consider this further in the next section.

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 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 size (TNA, which is in log form to mitigate the effects of very large funds) 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.

We 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% 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 other possibility is 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 155% (untabulated) across the lower deciles. 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 lagged performance for HQ funds.

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 B_t. Roll forward through December 2004 as the left-hand side to produce a time series of B_t. Finally, we calculate a standard t-statistic using that time series. The overlapping of the right-hand-side variables can produce a mild serial correlation in the time series of B_t so we employ the variance estimator of Gallant (1987) which is robust under serial correlation and heteroskedasticity.[10] 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. The other cases yield 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 and lagged 48-month performance are all positive, with all t-statistics above 3.0. Only two other variables display explanatory power for future returns. Expenses are negatively related to future performance, and size (ln(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 Panel A

[10] The bandwidth employed by the estimator is determined using the method suggested by Andrews (1991) assuming an AR(1) process and using equations (6.2) and (6.4) of Andrews. Following Andrews' recommendation, we examine several alternative bandwidths by adding ± 1 and ± 2 standard deviations to the autoregressive parameter. Our findings are robust across the various bandwidths.

vary from 0.2 to 0.5 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 size, 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 seems warranted.

Panel B of Table 8 also shows that abnormal performance persists strongly across HY funds, again lasting several years. The impact of expenses on returns to HY funds is strongly negative and is closer to a one-to-one relation. The remaining characteristics (turnover, load, and age) display no 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. It seems that the superior skill of the winning managers is responsible for most of the performance difference.

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. The performance of both winners and losers using gross returns persists for over four years (across ranking and holding periods). Stale prices can potentially generate only short-term effects, as the resolution of the staleness should rarely take more than a couple of months. The persistence of the HY loser funds net of expenses, as well as the spread between the winners and the losers, lasts for years also and is more than fund expenses or trading costs can account for. Nevertheless, we examine the issue of stale pricing and its potential effects on fund performance.

First, we examine fund performance net of expenses by modifing our models to include one-month-lagged factors. Although we earlier find little unconditional support for using the lags, we examine here if winner, loser, and the winner-minus-loser portfolios display 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. Across these specifications of persistence tests, we find no evidence of the equally weighted calendar-time portfolios of winners, losers, or winners minus losers loading on the lagged terms. The point estimates on the spreads in alphas between winners and losers are affected little, remaining large and highly significant. The evidence of the winner funds winning, net of expenses, weakens though.

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% (check the units). 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.[11] 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. We find that including family fixed effects produces mixed results. Specifically, we are unable to conclude whether the variation driving persistence in Table 8 is within-family or

[11] Interestingly, serial correlation for the HY winners and losers are roughly 0.30 when examining the factor-adjusted returns of the equally weighted portfolios. Other deciles display similar fund-level autocorrelation, yet the winners and losers are the only deciles to display high autocorrelation at the portfolio level.

inter-family since some regression specifications find no persistence when fixed effects are included while others find results nearly identical to those in Table 8.

7 Smart Money

Given our findings of persistence in the performance of corporate-bond funds, investors can possibly 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 realize 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 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 (0 to 1) of each fund based on performance according to the 2-factor model over $[t-12, t-1]$. We then estimate the following linear regression piecewise over deciles of lagged performance.

$$Pflow_t \quad = \quad b_0 + \sum_{d=1}^{10} b_d RANK^d_{[t-12,t-1]} + c_1 Pflow_{[t-12,t-1]} + \mathbf{c}_2 \mathbf{X}_{t-1} + \epsilon_t \tag{7}$$

where

$$\begin{aligned} RANK^1 &= \min(\text{rank}, 0.1) \\ RANK^{d \neq 1} &= \begin{cases} 0 & \text{if rank} < \frac{d}{10} \\ \min\left(\text{rank} - \frac{d}{10}, 0.10\right) & \text{if rank} \geq \frac{d}{10} \end{cases} \end{aligned}$$

and $\mathbf{X}_{t-1}$ is a vector of characteristics sampled at $t-1$ comprised of ln(TNA), 12b-1 fees, expenses minus 12b-1 fees (non12b-1), load dummy, and turnover. The regression is estimated each month, and the time-series of coefficient estimates is used to test that the mean coefficients are zero. We employ the variance estimator of Gallant (1987) which is robust under serial correlation and heteroskedasticity.[12] 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. We see that the well-documented convexity in the flow-performance relation for equity funds also exists for corporate-bond funds. The sensitivity of flows to lagged performance is highest for the top decile of HQ funds (0.06 with a t-statistic of 2.57) and is more than double the point estimates for any other HQ decile. HY funds show similar convexity at the top-end of prior performance. Interestingly, at the bottom-end of lagged performance, HY flows also 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.[13]

In short, flows of assets in corporate-bond funds chase past performance, as flows in equity funds do. Combining this with the evidence in sections 5 and 6 that relative performance across HQ and across HY 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).

[12] See footnote 10

[13] Sirri and Tufano (1998) examine yearly changes in flow so their point estimate of the coefficient on the best-performing funds is notably larger than our monthly estimate.

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 always, 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 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. To do so, we estimate the following regression each month.

$$\begin{aligned} AR_{t+k} &= b_0 + b_1 Dflow_{[t-3,t-1]} + b_2 AR_{[t-3,t-1]} + b_3 AR_{[t-12,t-4]} \\ &\quad + b_4 AR_{[t-24,t-13]} + \mathbf{cX_{t-1}} + \epsilon_t \end{aligned} \tag{8}$$

where AR_{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 ln(TNA), expenses, load dummy, and turnover.[14] We use three past horizons of AR on the right-hand side to address if flow provides any information regarding future performance beyond the information contained in past 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 $[t-24, t-13], [t-12, t-4]$, and $[t-3, t-1]$. 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 (6.1) that avoids overlapping the left-hand side variable. The two future periods we consider for AR_{t+k} are the next 3 months and the next 12 months, as in Table 10.

Table 11 reports the regression results for performance based on the 2-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. In short, smart money in the 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 inivestors as smart. Our findings simply indicate that HY fund investors chase performance profitably.

[14] Using percentage flow alters none of our findings.

8 Conclusion

The ability of past fund performance to forecast future performance is an important and often-addressed issue. However, the literature has not yet come to a consensus. The reason is that we must take a stand on what the source of momentum in the underlying stock returns is, and that topic seems far from settled. Similarly, momentum clouds the evidence on whether sophisticated fund investors are able to identify the better funds.

To address the questions of whether performance persists and whether some fund investors are sophisticated, we examine corporate-bond funds where the underlying securities' returns are devoid of momentum. There we find evidence of both persistence in performance and of a subset of investors that takes advantage of the persistence to select funds which perform better in the future.

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. The 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.[15] 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.

[15] 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 sort each of these 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 high portfolios minus the average return of the two low 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.

$$R_t = \alpha + \beta_1 GC_t + \beta_2 HY_t + \epsilon_t \tag{9}$$

A.3 Six-Factor Model

Our fourth 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.[16]

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

[16]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

$$\begin{aligned} R_t &= \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_4 OPTION_t \\ &\quad + \beta_5 ILI_t^{MCP} + \beta_6 CPI_t^{MCP} + \epsilon_t \end{aligned} \qquad (10)$$

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 estimates.

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 first four previous models (excluding the four-factor model which is nested in the six-factor model) are extended to include a timing parameter as follows. In the Treynor-Mazuy case,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k F_{kt}^2 + \epsilon_t \qquad (11)$$

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,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k \max(0, F_{kt}) + \epsilon_t \tag{12}$$

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.[17]

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

$$R_t = \alpha + \sum_k \beta_{kt} F_{kt} + \epsilon_t \tag{13}$$

where

$$\beta_{kt} = b_k^1 + b_k^2 Z_{t-1}. \tag{14}$$

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 four baseline models above as follows.

$$R_t = \alpha + \sum_k b_k^1 F_{kt} + \sum_k b_k^2 \left(F_{kt} \otimes Z_{t-1}\right) + \epsilon_t. \tag{15}$$

[17] 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.[18] 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.[19]

[18] 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.

[19] 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

This table presents the statistical distribution of annual returns. In Panel A and Panel B, we report the statistical distributions of the net annualized returns of high-quality and high-yield corporate bond funds, respectively, over three subperiods (1990-1994, 1995-1999 and 2000-2004) as well as for the full time period (1990-2004). In Panel C, we report the annualized factors returns used as benchmarks over the full time period (1990-2004).

	N	MeanRet(%)	MedianRet(%)	StdDev	Skewness	Kurtosis
Panel A : High-Quality Bond Funds						
1990 – 1994	1572	4.42	5.35	6.58	0.19	-0.21
1995 – 1999	3839	5.74	5.78	5.48	0.45	0.79
2000 – 2004	5492	5.33	5.05	3.20	0.35	0.97
All	10903	5.34	5.31	4.71	0.33	1.52
Panel B : High-Yield Bond Funds						
1990 – 1994	478	8.05	9.49	15.62	0.10	-0.26
1995 – 1999	1101	7.01	7.00	7.08	-0.38	-0.07
2000 – 2004	2009	4.85	4.32	11.32	-0.07	0.55
All	3588	5.94	5.61	11.01	-0.02	0.98
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

This table presents the means of various characteristics and holdings of high-quality and high-yield corporate bond funds. The age of the fund is in years, TNA represents the amount under management (reported in millions), the load and expense ratios are in percents. Average holdings information is also provided and is reported as a percentage of the funds holdings. In Panel A and Panel B, we report the means of high-quality and high-yield corporate bond funds, respectively, over three subperiods (1990-1994, 1995-1999, and 2000-2004) as well as for the full time period (1990-2004).

	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	6.94	235.84	1.26	1.86	0.83	42.25	37.96	1.61	0.82	0.36	0.27	9.74	5.24
1995 – 1999	5.61	216.33	1.70	1.49	0.94	41.49	38.67	0.62	0.69	0.44	0.39	6.84	9.85
2000 – 2004	7.31	326.04	1.70	1.56	0.99	50.44	33.53	0.85	0.18	0.38	0.33	6.42	6.06
All	6.62	259.40	1.57	1.64	0.92	45.11	36.53	0.93	0.52	0.40	0.34	7.35	7.33
Panel B : High-Yield Bond Funds													
1990 – 1994	9.68	353.54	0.90	3.56	1.27	83.48	2.01	1.52	0.85	1.84	2.06	5.65	2.10
1995 – 1999	6.59	390.23	1.08	2.81	1.35	84.12	1.71	0.01	1.74	1.49	3.23	5.10	1.96
2000 – 2004	7.16	273.69	1.02	2.42	1.32	84.85	2.74	0.01	1.02	1.42	2.53	4.79	1.76
All	7.81	339.16	1.01	2.93	1.31	84.25	2.18	0.36	1.26	1.54	2.69	5.11	1.91

Table 3. Performance of Net Returns

Panel A reports the statistics from calculating the cross section of monthly risk-adjusted performance (net of expenses) for the full sample as well as for an equally-weighted portfolio (EW) of all available funds each month over the full sample period. We report results for both high-quality and high-yield funds using three different performance-evaluation metrics (two-factor model, four-factor model, and style model) as described in the text. Panel B reports 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 of α	0.10	0.10	0.11	0.27	0.27	0.26
Fraction with $\alpha > 0$	0.10	0.05	0.04	0.09	0.07	0.12
Fraction with $\alpha < 0$	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	-0.06	-0.05	-0.04	-0.03	-0.02
t-stat	(-1.37)	(-5.87)	(-4.67)	(-0.79)	(-0.83)	(-0.51)

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		
EGB4	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

Panel A reports the statistics from calculating the cross section of monthly risk-adjusted performance (gross of expenses) for the full sample as well as for an equally-weighted portfolio (EW) of all available funds each month over the full sample period. We report results for both high-quality and high-yield funds using three different performance-evaluation metrics (two-factor model, four-factor model, and style model) as described in the text. Panel B reports 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 of α	0.10	0.10	0.11	0.26	0.24	0.23
Fraction with $\alpha > 0$	0.40	0.26	0.22	0.24	0.21	0.31
Fraction with $\alpha < 0$	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	0.02	0.03	0.08	0.07	0.06
t-stat	(2.48)	(2.50)	(2.27)	(1.28)	(1.52)	(1.36)

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		
EGB4	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

In this table, we report the results of persistence tests using both net and gross returns for high-quality corporate bond funds. Each month starting in 1992, we rank funds into ten equally weighted portfolios based on their lagged 12-month performances. Panel A, B and C represents the results when past performance is measured using the 2-factor model, the 4-factor model, or the style model, respectively. We then estimate the future performance of the top decile (winner), the bottom decile (loser), and the returns spread between these two. For each ranking method, we evaluate the post-ranking performances over either the next month or the next forty-eight months using all three models. The t-statistics are in parentheses and are robust to heteroskedasticity and autocorrelation.

	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

In this table, we report the results of persistence tests using both net and gross returns for high-yield corporate bond funds. Each month starting in 1992, we rank funds into ten equally weighted portfolios based on their lagged 12-month performances. Panel A, B and C represents the results when past performance is measured using the 2-factor model, the 4-factor model, or the style model, respectively. We then estimate the future performance of the top decile (winner), the bottom decile (loser), and the returns spread between these two. For each ranking method, we evaluate the post-ranking performances over either the next month or the next forty-eight months using all three models. The t-statistics are in parentheses and are robust to heteroskedasticity and autocorrelation.

	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	0.115	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 Portolios Ranked on 12-Month Performance

This table reports the means of the fund characteristics within each decile portfolio formed from the two-factor adjusted returns over the prior twelve months. The two-factor alpha (α) and the raw return are from the first month following portfolio formation. Panel A and Panel B present the results for high-quality and high-yield corporate-bond funds, respectively.

Group	Load	Age (Years)	TNA (logs)	Exp. Ratio	Turn-over	Raw Return	α	t stat
Panel A : High-Quality Bond Funds								
1-Winner	1.24	8.86	4.72	0.07	2.06	0.58	0.04	(1.33)
2	1.20	9.47	4.70	0.06	1.61	0.52	0.02	(0.73)
3	1.26	9.00	4.59	0.06	1.78	0.51	0.01	(0.30)
4	1.34	8.49	4.46	0.07	1.69	0.50	0.00	(-0.04)
5	1.47	8.41	4.32	0.07	1.57	0.49	-0.02	(-0.86)
6	1.60	8.12	4.11	0.07	1.46	0.48	-0.02	(-1.24)
7	1.80	8.30	3.97	0.08	1.38	0.48	-0.03	(-1.60)
8	1.86	8.23	3.83	0.09	1.45	0.48	-0.04	(-1.56)
9	2.16	8.28	3.64	0.09	1.49	0.46	-0.07	(-2.68)
10-Loser	2.36	8.84	3.58	0.10	1.57	0.43	-0.14	(-3.52)
Panel B : High-Yield Bond Funds								
1-Winner	2.59	10.70	4.96	0.10	1.16	0.81	0.17	(2.48)
2	3.06	10.52	4.94	0.10	1.08	0.72	0.07	(1.31)
3	3.18	10.29	4.97	0.10	1.04	0.69	0.04	(0.73)
4	3.25	9.96	4.98	0.11	0.99	0.64	-0.03	(-0.46)
5	3.32	10.25	5.06	0.11	0.92	0.64	-0.02	(-0.39)
6	3.19	9.98	5.02	0.10	0.92	0.61	-0.05	(-0.97)
7	3.18	9.75	5.03	0.11	0.86	0.59	-0.08	(-1.55)
8	3.15	9.36	5.03	0.11	0.95	0.56	-0.12	(-2.15)
9	3.21	9.14	4.88	0.12	1.00	0.49	-0.20	(-3.13)
10-Loser	3.06	9.39	4.45	0.12	1.16	0.27	-0.43	(-5.39)

Table 8. Future Fund Performance and Fund Characteristics

In this table, we assess the relation between future performance (12 months) as it relates to lagged fund characteristics (expenses, turnover, size, and the existence of a load). To avoid overlapping both sides of the regression and creating a serial correlation in the cross-sectional coefficients, we use an approach which is akin to a calendar-time portfolio method. To do this, we regress the cross-section of one-month risk-adjusted returns on the lagged control variables. Specifically, using the same left-hand side variable, we roll back the right-hand side variables back one period at a time [t-1,t-12] to create 12 separate beta estimates for right-hand side coefficients. Next, estimate the average of the twelve beta estimates. This average then provides a summary of how lagged 12-month performance relates to future 12-month performance. Finally, we roll the left-hand side variable forward one month and repeat to create a time-series of the beta estimates. We use the fund characteristics found in Table 7 as well as Alpha01 (the performance over months $[t-12, t-1]$) and Alpha02 (the performance over months $[t-48, t-1]$) as the control variables. We report results using both the 2-Factor and Style analysis to assess both the lagged performance and the future performance. The t-statistics are robust under serial correlation and heteroskedasticity.

	On Lagged 2-Factor Alphas		On Lagged Style Alphas	
Dep. Var.	$AR^{2-factor}_{[t,t+11]}$	$AR^{style}_{[t,t+11]}$	$AR^{2-factor}_{[t,t+11]}$	$AR^{style}_{[t,t+11]}$
	Panel A: High-Quality Funds			
Alpha01	0.20		0.20	
	(3.49)		(4.46)	
Alpha02		0.33		0.23
		(5.19)		(3.18)
Loaddum	0.00	0.00	0.01	0.01
	(0.15)	(0.50))	(1.43)	(1.61)
Age	0.00	0.00	0.00	0.00
	(0.33)	(0.69)	(-0.94)	(-0.76)
Size	0.01	0.01	0.01	0.01
	(3.04)	(2.68)	(3.37)	(3.12)
Expense	-0.43	-0.31	-0.48	-0.43
	(-2.37)	(-1.65)	(-3.94)	(-3.44)
Turnover	0.00	0.00	0.00	0.00
	(0.88)	(0.27)	(1.47)	(1.75))
Adj R^2	0.29	0.28	0.18	0.18
	Panel B: High-Yield Funds			
Alpha01	0.20		0.20	
	(4.16)		(3.57)	
Alpha02		0.41		0.41
		(4.73)		(4.64)
Loaddum	-0.02	0.00	-0.03	-0.01
	(-0.85)	(-0.05)	(-0.97)	(-0.20)
Age	0.00	0.00	0.00	0.00
	(0.57)	(0.50)	(0.72)	(0.79)
Size	0.01	0.00	0.01	0.01
	(0.83)	(0.64)	(1.46)	(1.04)
Expense	-0.98	-0.87	-0.71	-0.68
	(-3.67)	(-3.17)	(-2.01)	(-1.89)
Turnover	0.05	0.05	0.03	0.03
	(1.56)	(1.61)	(0.93)	(0.96)
Adj R^2	0.36	0.35	0.26	0.25

Table 9. Regressions of Net Flow on Prior Performance

In this table, we analyse if corporate bond fund investors chase prior performance. The left-hand side variable is the percentage flow to a fund in month t. The control variables include prior performance, which is determined by ranking the funds into deciles over the t-12 to t-1 period [denoted as G10 through G1]. Other control variables include lagged fund flow, size, 12b-1 fees, expenses minus 12b-1 fees, load dummy, and turnover calculated at t-1. The regression is estimated each month, and we then test the significance of the time-series of coefficients. The t-statistics are robust under serial correlation and heteroskedasticity.

	High-Quality Funds	High-Yield Funds
12b1fee	0.01	0.00
	(0.50)	(0.23)
Expenses (less 12b1)	-0.04	-0.05
	(-3.14)	(-3.27)
Loaddum	0.00	0.00
	(-0.70)	(0.22)
Size	0.00	0.00
	(-4.69)	(-7.81)
$\text{Flow}_{[t-12,t-1]}$	0.04	0.04
	(15.27)	(11.68)
G1 (lowest)	0.00	0.09
	(-0.05)	(3.24)
G2	0.03	0.02
	(2.30)	(0.97)
G3	0.01	0.04
	(0.67)	(2.18)
G4	0.01	-0.01
	(0.86)	(-0.79)
G5	0.00	0.02
	(-0.05)	(1.28)
G6	0.01	0.00
	(0.84)	(-0.17)
G7	0.01	0.02
	(1.57)	(1.18)
G8	0.00	0.02
	(-0.11)	(1.09)
G9	0.01	0.02
	(1.15)	(0.91)
G10 (highest)	0.06	0.07
	(2.57)	(2.52)
Adj R^2	0.22	0.41

Table 10. Smart Money

In this table, we examine if smart money exists in bond funds. We separate funds with inflows and outflows over the prior three months. We then examine the performance of these funds over future holding periods. Specifically, each month we form two equal-weighted and two flow-weighted portfolios of bond funds based on their lagged 3-month net flows. One portfolio of funds with positive net flow is formed (Inflow), and another portfolio of funds with negative net flow is formed (Outflow). These portfolios are held for 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. As always, we use calendar-time portfolios, averaging the returns of the portfolios in each calendar month that are in the holding periods. The t-statistics are in parentheses and are robust to heteroskedasticity and autocorrelation.

	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. Regressions of Performance on Prior Flow and Prior Performance

We examine how future abnormal performance is related to prior characteristics. We measure future abnormal return over $AR_{[t,t+2]}$ and $AR_{[t,t+11]}$ periods using either the two-factor or style models. The control variables are the dollar flow for a given fund over the prior three months, ln(TNA), expenses, load dummy, and turnover at month t-1. Additionally, we include three past horizons of abnormal returns to address the issue if flow provides any information regarding future performance beyond the information contained in past performance. $\alpha_{[t-j,t-k]}$ is the 2-factor adjusted return over the months denoted. We continue to use a procedure that avoids overlapping returns, and we use a separate, rolling twenty-four month window to estimate the factor loadings that determine each alpha. The *t*-statistics are in parentheses and are robust to heteroskedasticity and autocorrelation.

	$AR_{[t,t+2]}$	$AR_{[t,t+11]}$	$AR_{[t,t+2]}$	$AR_{[t,t+11]}$
	High-Quality Funds		High-Yield Funds	
$\text{Flow}_{[t-3,t-1]}$	0.001	0.000	-0.003	-0.001
	(0.836)	(0.278)	(-0.583)	(-0.182))
$alpha_{[t-3,t-1]}$	0.067	0.092	0.185	0.120
	(1.428)	(3.697)	(4.910)	(5.687)
$alpha_{[t-12,t-4]}$	0.203	0.113	0.210	0.093
	(2.739)	(2.399)	(3.209)	(1.610)
$alpha_{[t-24,t-13]}$	0.019	0.074	-0.061	0.058
	(0.296)	(1.473)	(-0.907)	(1.034)
Loaddum	-0.003	0.002	0.001	0.005
	(-0.334)	(0.252)	(0.033)	(0.127)
Age	0.000	0.000	0.001	0.001
	(0.158)	(0.223)	(0.812)	(0.723)
Size	0.004	0.006	-0.002	0.005
	(1.668)	(2.641)	(-0.287)	(0.652)
Expense	-0.455	-0.438	-0.568	-0.854
	(-2.829)	(-2.743)	(-2.032)	(-3.424)
Turnover	0.004	0.002	0.045	0.035
	(1.002)	(0.511)	(1.959)	(1.316)
Adj R^2	0.383	0.367	0.432	0.417