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On Economies of Scale and Persistent Performance in Corporate-Bond Mutual Funds

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Abstract

Studies of stock mutual funds find little evidence of persistence in performance. The most common interpretation for such limited persistence is that dispersion in performance is driven largely by managers' luck. However, Berk and Green (2004) contend that managers are skilled and limited persistence is due to diseconomies of scale in mutual funds. In contrast to the findings of diseconomies of scale in stock mutual funds, we find no relation between performance and lagged fund size in corporate-bond mutual funds. Without diseconomies, bond funds display persistence in performance that is long-lived. Prior winners outperform prior losers for the next four years, net or gross of expenses. Moreover, prior winners generate positive alpha gross of expenses for the next four years. This persistence in performance is evident controlling for various fund characteristics and seems largely due to differences in managers' skills, as opposed to luck.

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Abstract

Studies of stock mutual funds find little evidence of persistence in performance. The most common interpretation for such limited persistence is that dispersion in performance is driven largely by managers' luck. However, Berk and Green (2004) contend that managers are skilled and limited persistence is due to diseconomies of scale in mutual funds. In contrast to the findings of diseconomies of scale in stock mutual funds, we find no relation between performance and lagged fund size in corporate-bond mutual funds. Without diseconomies, bond funds display persistence in performance that is long-lived. Prior winners outperform prior losers for the next four years, net or gross of expenses. Moreover, prior winners generate positive alpha gross of expenses for the next four years. This persistence in performance is evident controlling for various fund characteristics and seems largely due to differences in managers' skills, as opposed to luck.

1 Introduction

One potential benefit that mutual funds provide their investors is economies of scale. Pooling money across a large number of small investors should lead to a per share reduction in fixed costs, such as operational expenses and research. However, large asset bases can also bring about diseconomies of scale given a finite set of investment opportunities. While there are many aspects to economies of scale in mutual funds, Chen, Hong, Huang, and Kubik (2004) document that the return performance of stock funds decreases with fund size. That is, on net, there are diseconomies of scale in stock funds. They attribute much of this diseconomy of scale to trading costs. Examining this notion more directly, Edelen, Evans, and Kadlec (2007) and Yan (2008) find that trading costs increase as the size of stock funds increases, indicating that trading costs play a large role in the documented diseconomies of scale in stock funds.

Stocks trade in organized exchanges while corporate bonds trade in an over-the-counter, less transparent dealer market. One consequence of this difference in trading environments is that the relation between trading costs and trade size differs for stocks and bonds (Green, Hollifield, and Schuroff (2007), Bernhardt, Dvoracek, Hughson, and Werner (2005)). In the stock market, trading costs increase with trade size. In the bond market, they decrease.[1] For example, Edwards, Harris, and Piwowar (2007) find that the average roundtrip cost of executing a $1 million trade in the corporate bond market is 8 basis points higher than the cost to execute a $2 million trade. Perhaps even more glaring is the fact that the 8 basis point difference represents a 44% reduction in trading costs as trade size goes from $1 to $2 million. Therefore, large corporate-bond mutual

[1] Bernhardt, Dvoracek, Hughson, and Werner (2005) cite many studies finding the positive relation in the stock market. They also note that the London Stock Exchange (LSE) instead displays a negative relation between trade size and costs, more akin to bond markets since the LSE (in 1991) is a more opaque stock dealer market. Keim and Madhavan (1997) and Chan and Lakonishok (1997) find that the costs of institutional management firms to trade U.S. stocks increase in trade size. For corporate bonds, Schultz (2001), Bessembinder, Maxwell, and Venkataraman (2006), and Edwards, Harris, and Piwowar (2007) detect a negative relation between trade size and costs.

funds enjoy an economy of scale that stock funds do not. We examine whether this unique size advantage removes the diseconomies of scale from corporate-bond funds.[2]

In addition to the findings on trading costs, anecdotal evidence also suggests that stock and bond funds might differ regarding diseconomies of scale. Fidelity is a giant in the retail industry but a smaller player on the institutional side. For decades both retail and institutional funds were run side by side at Fidelity, but in 2005 Fidelity carved out a money management firm dedicated solely to institutional clients, called Pyramis Global Advisors. To promote and foster the independence of Pyramis, especially in the eyes of potential clients, Fidelity built a $200 million facility to house all institutional trading and operations in Rhode Island, away from Fidelity's home in Boston. However, Pyramis focuses only on stock and real estate investing; its fixed-income assets remain managed in Boston. "When (Fidelity CEO) Johnson and (COO) Reynolds created Pyramis, they left management of the institutional fixed-income group with the corporate parent because of economies of scale" (Kahn (2008)).[3]

Using a sample of over 1,200 corporate-bond mutual funds from 1990 to 2004, we find that the performance of these funds is unrelated to lagged fund size, in contrast to the stock fund results of Chen, Hong, Huang, and Kubik (2004). (We refer to corporate-bond mutual funds as simply bond funds throughout the paper.) Our interpretation of this result is that the economies of scale in trading costs are offset by diseconomies of scale in other dimensions. For example, investment opportunities (mispricings) are

[2]Municipal bonds also display a trade cost function which decreases in trade size. Biais and Green (2007) review the literature on municipal bond trading and provide a historical perspective on the development of dealer markets for bonds. We examine only corporate-bond funds in this study. Corporate bonds are similar to stocks in that both securities are claims on the underlying firm's assets. Corporate-bond funds seem to offer a more useful comparison to stock funds in that the skill set necessary to generate abnormal returns can be similar. Also, we are unaware of evidence regarding trade size and costs for Treasury and other government bonds, which are traded in more liquid markets.

[3]We thank Diane Del Guercio for this example. To the extent that a fund closing to new investors is due to strains on future investment opportunities or performance, other anecdotal evidence that bond funds incur lower diseconomies of scale is provided by the relatively infrequent closing of bond funds to new investors, as found by Zhao (2004).

limited or increasingly costly to find. Regardless, our first finding is that bond funds display no overall diseconomies of scale.

The fact that bond funds display no diseconomies of scale is particularly noteworthy because of the implications for persistence in bond fund performance. Berk and Green (2004) employ diseconomies of scale to explain why performance across mutual funds should not persist in a competitive labor market even when there are true differences in skill across fund managers. Specifically, in their model, fund flows chase prior fund performance and the increase in the size of the best-performing funds triggers the diseconomies of scale that offset the skill of the fund manager, resulting in zero abnormal performance for the fund in equilibrium. Their result is striking because most studies of stock funds conclude that there is little persistence in the performance of stock funds. That is, stock fund performance is a short-lived phenomenon typically lasting one year without controlling for momentum in the underlying stock returns, and even shorter lived after controlling for momentum (Carhart (1997), Bollen and Busse (2005), Fama and French (2008)).[4] Additionally, Busse, Goyal, and Wahal (2009) find similar persistence results for stock portfolios managed by institutional investment firms.

Diseconomies of scale are the mechanism in Berk and Green's (2004) model, along with assets flowing into prior winner funds, that eradicates persistence in performance. Without diseconomies, performance would persist. Of course, the alternative hypothesis for why the evidence of persistence in stock fund performance is limited is that fund managers generally lack skill, which seems to be the most common interpretation. In short, bond funds offer an out-of-sample test of Berk and Green's (2004) theory. Consistent with their theory, we find that, without diseconomies of scale, the performances

[4] Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhasuer (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Malkiel (1995), Elton, Gruber, and Blake (1996) and others also study persistence in stock fund performance.

of bond funds persist for at least four years, before and after expenses.[5] Note that the long-lived persistence in bond-fund performance is not due to other observable fund characteristics because we control for these in our analysis. Our regression models indicate that about 20% of abnormal performance over the past year (or past four years) remains for the next four years. Moreover, we find that funds in the top decile of prior performance continue to generate positive alphas before expenses that range from 5 to 10 basis points per month for four years. These findings stand in stark contrast to the evidence on persistence in stock fund performance.[6]

The magnitudes of the lasting disparities we detect in performance across winners and losers are material in the bond market, as they represent about 15% to 30% of the monthly risk premiums (return in excess of the risk free rate) earned on the high-quality and high-yield bond asset classes over our sample period. Another way to appreciate these magnitudes is to realize that the cross-sectional standard deviation in bond fund alphas is about 10 basis points per month. Therefore, a fund's performance ranking would shift notably if even 5 basis points per month were added, or subtracted, from its performance.

Finally, we also examine the flow-performance relation for bond funds. As in stock funds, bond-fund flows chase performance, with the top quintile of funds receiving larger inflows. So bond-fund investors behave similarly to stock-fund investors, yet diseconomies of scale do not arise. Assuming that diseconomies of scale must exist at some critical threshold of size (outside the range of fund sizes in practice), we conclude that flows in bond funds are not chasing past performance enough.

[5]Huij and Derwall (2008) find persistence in bond-fund performance for up to one year but do not examine longer horizons. 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. Blake, Elton, and Gruber hesitate to conclude that persistence is a general feature of bond funds.

[6]To further contrast the disparity in performance persistence across stock and bond funds, Fama and French (2008) find that any evidence of stock-fund persistence is difficult to come by after 1992, which roughly aligns with our sample period.

In sum, persistence in the performance of corporate-bond funds is long-lived, in contrast to stock funds. Further, the performance difference across funds seems due to skill, as the winner funds are able to generate positive alphas for the next four years before considering fund expenses.

In the next section, we detail our metrics for performance evaluation, and in section 3, we discuss the sample. Section 4 finds that corporate bond funds display no evidence of diseconomies of scale. Section 5 examines the persistence of these bond funds. In section 6, we examine the sensitivity of fund flows to prior performance. Section 7 concludes the paper.

2 Performance-Evaluation Methods

In this section, we detail our methods to assess the performances of corporate-bond mutual funds. Since there is no consensus about which methods are best, we examine performance using a variety of models. 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 (risk premium), 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.

We focus our analyses on three of the performance-evaluation models that we considered. The other performance models are described in section A.1 of the Appendix, and are combinations of alternative factors, conditional factor loadings, and market-timing specifications. We find that the average performance of bond funds in the Appendix models are similar to those across the three models we employ throughout the paper, so we exclude the Appendix models for the sake of brevity. The three models of performance evaluation that we employ are as follows.[7]

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).

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

2.2 Style Analysis

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

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

[7] For interested readers, we report our performance findings for the average bond fund in section A.2 of the Appendix.

where Var[·] is the variance operator, R_t^k is the excess return on asset k and β_k is the weight on asset class k that minimizes the tracking error 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.[8]

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

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

[8]We discuss the two macroeconomic factors in section A.1.2 of the Appendix.

3 Sample of Corporate-Bond Funds

Our sample is from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database and 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 beginning in 1993. Following the conventions of prior research, as well as the practitioner's view of bond asset classes, we divide the sample into those funds concentrating in high-quality bonds and those concentrating in high-yield bonds.[9] Finally, we require funds to have at least 24 return observations so that the performance-evaluation models can be reasonably estimated. The 24-month requirement imparts no noticeable survivorship bias on performance. Specifically, the alpha of the equally weighted portfolio of all funds with at least 24 months of returns is nearly identical to the alpha of the equally weighted portfolio of all funds.[10]

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

[10]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. Also, we have examined other data filters and find no material differences between the filtered sample and our main sample regarding average fund performance and return persistence. The filter removes funds with: (i) lower than $10 million dollars of total net assets last year, or (ii) with greater than 10% of their holdings in stock last year, or (iii) with an R^2 from a given factor model lower than 0.20.

For fund returns net of expenses, we execute studies at the share-class level. For returns gross of expenses, our analyses are at the fund level. We do this for both robustness and completeness.

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

Panel C of Table 1 reports return properties over the full sample period for the seven factors we use in the various models of performance evaluation. The Aggregate and Government indices deviate little from each other, with the High-Quality index also relatively close. The High-Yield index, however, has a standard deviation of return (12.55% per year) that is roughly double that shown by the three prior indices, 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 indices. As such, their average returns are small, but the Default index does display a rather large standard deviation of return of 12.35%.

Table 2 provides several characteristics of the funds over the sample period, namely mean age, fund and family size, turnover, load, and expense ratio. Family size is the cumulative total net assets of all other bond funds in the fund's family, excluding the given fund. We also report the mean portfolio weights across a number of asset classes. As expected, corporate and government bonds together comprise roughly 80% of high-quality funds, while corporate bonds alone comprise over 80% of the holdings of high-yield funds. The remaining bond and stock categories receive little weight. In fact, cash is the next largest category for both high-quality and high-yield funds, roughly 7% and 5% respectively. We can surmise from Table 2 that accounting for the performances of asset classes other than government and corporate bonds should not materially affect our results.

Table 2 also reports the pairwise correlations of fund characteristics. Fund TNA is strongly correlated with several fund characteristics, specifically age, expense ratio, load, and family TNA. These correlations indicate that controlling for these other characteristics is important when examining the relation between fund TNA and future performance.

4 Economies of Scale

4.1 Portfolio Evidence

As a preliminary investigation of economies of scale, we examine the relation between lagged fund size and future performance without controlling for other characteristics. Each month we sort funds into quintiles based on fund TNA. We then calculate an equally weighted return each calendar month for funds that are in months $t + 1$ to $t + 12$.[11] Standard errors for the t-statistics are estimated using Newey and West's (1987) procedure with six lags.[12]

[11]The findings do not materially change when we consider net performance in month $t + 1$ only.

[12]Employing zero or twelve lags does not alter the findings. This is also true for our main findings throughout the rest of the paper.

Table 3 reports the mean sizes and performances of the five size portfolios. Panel A shows evidence of economies of scale in high-quality bond funds, with return spreads net of expenses between the large and small funds of about 0.06% per month and t-statistics above 5.24 across all four performance metrics. We add raw returns to our set of metrics as a simple, albeit noisy, robustness check on the performance differences. In addition to the sizable spread between large and small fund performance, Table 3 also shows that the performance is generally decreasing as size decreases, further demonstrating a positive relation between size and performance. As we will see shortly however, this evidence of economies of scale is due to the correlation of size with other characteristics. Also, the mean sizes shown in Panel A are similar to those reported by Chen, Hong, Huang, and Kubik (2004) for stock funds.

Panel B examines gross returns of the bond funds, before expenses are paid. To calculate monthly gross return, we divide the annual expense ratio by 12 and add that quantity to net monthly returns. The gross analysis is at the fund level. For funds with more than one share class, we calculate the asset-weighted expense ratio across all classes.

In Panel B, we see that the largest HQ funds statistically outperform the smallest according to gross performance as well. But, the relation between lagged size and gross performance is not very strong. The alphas deviate very little, if at all, across quintiles 1 to 4. This finding suggests that variation in expenses is strongly related to the size effect we see in Panel A. The regression tests in the next section will confirm this.

In Panels C and D, we examine the net and gross performances, respectively, of HY funds. There is no clear relation between the lagged size of HY funds and net or gross performance. The low performance of the middle quintile prevents us from concluding that there is a cursory negative size effect on HY fund performance. We turn to a more rigorous examination of the relation between fund size and future performance in the next section.

4.2 Regression Evidence

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

Roll the left-hand side forward to February 1992 and repeat the process of running twelve regressions for that month to obtain a second value for $\mathbf{B_t}$. Rolling forward through the sample period produces a time series of $\mathbf{B_t}$. Finally, we calculate a t-statistic using the standard error of the time series of each coefficient. The overlapping of the right-hand-side variables can produce a mild serial correlation in the time series of $\mathbf{B_t}$ so we employ the variance estimator of Newey and West (1987) with six lags. Also, note that expenses and turnover are sampled from the upcoming fiscal year, contemporaneous with future returns, since our goal is to explain the variation in future 12-month return. Flow is measured as

$$Flow_t = \frac{TNA_t - TNA_{t-12} \times (1 + r_{t-12,t-1}) - MGTNA_{t-12,t-1}}{TNA_{t-12}} \tag{6}$$

where TNA_t is a given fund's total net assets in month t, $r_{t-12,t-1}$ is the fund's net return over the prior 12 months, and $MGTNA_t$ is the increase in TNA due to fund mergers over the prior 12 months. Finally, for brevity, we examine only the 2-factor and style measures of performance.

Table 4 provides the results of the cross-sectional regressions. Controlling for other fund characteristics, we see no evidence of a relation between fund size and next year's fund performance for either HQ or HY funds. Recall that Table 2 shows that expenses, family size, and age each have correlations with fund size of about 0.3 in absolute value. Hence, the evidence of economies of scale in HQ funds shown in Table 3 dissipates when other fund characteristics are controlled for. The bottom line, however, is that the performances of both HQ and HY bond funds display no evidence of diseconomies of scale.

We can also see in Table 4 that other characteristics explain fund performance. As is well documented in studies of stock funds, such as Carhart's (1997) for example, expenses are negatively related to fund performance. Interestingly, this is the only variable that relates to HY fund performance, though the magnitude of the coefficients on the load dummy and age suggest that a lack of statistical power is the issue in that market. For HQ fund performance, family size (+), load dummy (−), age (−), and turnover (+) explain performance. The findings for family size and the load dummy are also detected in stock funds (e.g., Chen, Hong, Huang, and Kubik (2004) and Carhart (1997), respectively). Age though does not display a robust relation to stock fund performance (Chen, Hong, Huang, and Kubik (2004)).

In strong contrast to the stock fund literature, however, turnover is positively related to the performance of HQ bond funds. Carhart (1997) and others find a negative relation between turnover and stock fund performance. This contrast between stock funds and HQ bond funds might be linked to the different trading environments of the underlying securities and the differences in the trading cost structures. Specifically, the positive turnover-performance relation here might be due to bond dealers' competeting with each other on price for expected future order flow (Bernhardt, Dvoracek, Hughson, and Werner (2005)).

We also examine future alpha gross of expenses using the cross-sectional regressions. Some explanatory variables need adjusting to arrive at fund level measures. For funds with multiple share classes, fund size is aggregated over all share classes; expense ratios are the asset-weighted average across the share classes; load dummy is set to one if any share class has a load; age is the oldest of the share classes; and flow is calculated from fund-level size and asset-weighted net returns. The findings of the regressions using gross alpha are very similar to those in Table 4, and we do not tabulate them. Two exceptions are that the effect of age on the performance of HQ funds dissipates and flow is positively related to future gross alpha. Interestingly, expenses even have a negative relation with gross alphas, as Gil-Bazo and Ruiz-Verdu (2009) find for stock funds. Most importantly, lagged fund size remains unrelated to fund performance.

As an aside, we note that controlling for expenses in the regressions removes the explanatory power of fund size for HQ funds, consistent with the findings in Table 3. So economies of scale do manifest themselves through expenses, as the negative relation between fund size and expenses is well known (e.g., see Tufano and Sevick (1997) and Khorana, Servaes, and Tufano (2009)). However, this benefit of increased size, by definition, only manifests in performance net of expenses, not gross of expenses. Regardless, bond funds display no overall evidence of diseconomies of scale in their return performance, neither net nor gross of expenses.

5 Persistence in Performance

With bond funds not displaying diseconomies of scale, we consider whether performance persists in bond funds. That is, we examine whether the best performing corporate-bond funds in the past continue to perform well in the future, and whether the worst performing funds in the past continue to perform poorly in the future. We examine persistence in both net and gross performance, thereby separating the performance realized by the fund investors from any market-beating ability of the fund manager.

5.1 Portfolio Evidence

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 consider months

$(1-12)$, $(13-24)$, $(25-36)$, and $(37-48)$, respectively. For brevity, we tabulate only the 12-month and 48-month ranking periods, as the 24-month results are similar.

To examine holding-period performance over these multi-month windows, 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 post-ranking performance over months 1 to 12 for funds that are winners (top decile) over the given ranking period, we identify the portfolios of funds in calendar-month τ that are determined to be winners at each month-end of the prior 12 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 $\tau-12$ which is in the twelfth month of its holding period. We equally weight the returns in month τ across these 12 portfolios. This equally weighted return captures the performance of all funds in calendar-month τ that are currently in their 12-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.

To determine the winner and loser funds over a given ranking period, we sort all funds based on their performances over the ranking period according to the three factor models. For the 12-month ranking period, we use factor loadings over the prior 24 months. For the net performance of HQ funds, Panel A of Table 5 employs the 2-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). Panel B uses the style model for ranking. Ranking with the 4-factor model produces similar conclusions and is not tabulated.

Table 5 shows that performance in bond funds persists for at least four years. The (W-L) portfolio displays a positive alpha of about 10 basis points per month across all ranking periods (12 months, 48 months, and the untabulated 24 months), all performance metrics (2-factor, style, and the untabulated 4-factor models), and all horizons (year 1, year 2, year 3, and year 4). Note that there is little evidence of decay in performance from year 1 to year 4 across this myriad of test specifications.

The other consistent theme of Table 5 is that the winner funds have zero alpha on average while the losers have a significantly negative alpha for four years. Since the table examines net returns, these results are not very surprising (though the ability of winner funds to cover their expenses foreshadows their positive performance before expenses are considered).

Table 6 shows that performance persists for at least four years in HY funds too. However, there is more evidence of decay in the performance spread between the top and bottom deciles of funds. The spread is about 25 basis points per month in year 1 and falls to about 12 basis points in year 4 while remaining statistically significant. The findings are generally robust across all the specifications we consider, though some isolated cases have insignificant spreads, such as year 3 when ranking on prior 12 months.

In short, HY funds reveal the same general findings as HQ funds in Table 5, but we can again (as in Table 4) see statistical power issues in the HY sample, consistent with the increased volatility of HY funds shown in Table 1. For example, note that the 12-month winners in Panel A generate alphas of between 6 and 8.5 basis points per month over the first year, but are insignificantly different from zero.

Turning to persistence in gross returns, Table 7 shows that the return spreads between the winner and loser HQ funds persist again for at least four years. For brevity, we report performance over months 13 to 48 instead of each year separately. The individual years tend to not display significance, but this is a power issue. The point estimates do not vary much across the years, but alphas over months 13 to 48 display statistical significance, as shown in Table 7. The magnitudes of the alphas are about half of what they are for net returns, about 5 basis points per month with gross returns. This suggests that a portion of persistence is attributable to differences in expenses, which is not very surprising based on the mutual fund literature. Nevertheless, the 5 basis point spread in gross performance is economically material in the HQ bond market.

Also noteworthy is the finding that gross performance is positive for the winner funds over the next four years. This finding suggests that some managers can consistently beat the market in their trading of HQ corporate bonds. The alpha estimates range from 5 to 12 basis points per month over four years! This long lasting positive alpha stands in contrast to the findings in the stock fund literature.

Table 8 shows that spreads in gross returns across HY winner and loser funds also remain sizable over four years, maintaining an average spread of about 10 basis points per month over months 13 to 48. However, the ability of the winner funds to continue generating positive alpha in the future is not as robust in HY funds as in HQ funds. Curiously, we find some evidence that loser funds continue to generate negative gross alphas in year 1. Fama and French (2008) and others find this for stock funds too.

5.2 Characteristics of Lagged-Performance Deciles

The prior section shows that the relative performances of past winner and loser bond funds persist strongly into the future. In this section, we examine the performances of the remaining decile portfolios of funds. We also discuss several other fund characteristics to gain insights into why fund performance persists.

Table 9 provides the means of several characteristics, including net performance, for each decile of funds ranked on performance over the prior 12 months using the two-factor model. Maximum load, age, and fund and family size 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, month $t+1$.

First, we can see for both HQ and HY funds, in Panels A and B of Table 9 respectively, that future alpha (net of expenses) declines monotonically from the winner decile to the loser. This reinforces the strength of the persistence in performance documented in the prior section. Persistence is even evident in raw returns, as this measure declines monotonically too. We examine raw returns as another robustness check and find that persistence in performance is independent of the model of expected returns.[13] Comparing the return spreads between winners and losers in Table 9 to the spreads in Tables 5 and 6 reveals that the spread decays from month $t+1$ to the subsequent later months. Specifically, the difference in net alpha between HQ winners and losers is 0.17% in month 1 (Table 9), which declines to about 0.10% per month over months 1 to 12 (Table 5). For HY funds, the difference in net alpha is 0.58% in month 1 (Table 9) and about 0.35% per month over months 1 to 12 (Table 6). This reveals that a sizable portion of persistence in performance is temporary (which is possibly due to price pressure/illiquidity). Interestingly, even net of expenses, the winner HY funds provide a statistically positive alpha in month 1. We leave for further research an investigation into what drives the decay in persistence. Our focus here is on the persistence that is sustained over longer horizons.

Also in Table 9, we see that expense ratios (expressed per month) vary only slightly across winner and loser deciles compared to the return spreads across the top and bottom deciles, shown in Tables 5 and 6. Therefore, persistence across winner and loser funds is much more than just differences in expenses. Another potential explanation for the sustained relative performance is that the trading costs of the loser funds are

[13] Raw returns are however noisier measures of expected returns than the alphas we employ, and we do not advocate using them as a primary measure of performance. In support of this, we find that ranking on raw returns does not predict future alpha, but ranking on alpha predicts future raw return (and future alpha).

higher than those of the winners. Without data on transactions, however, we can only use portfolio turnover as a proxy for trading costs. Panel A of Table 9 shows that HQ winner funds have much higher turnover in the coming months than other funds, 206% per year on average versus the 155% averaged across the lower deciles (not in table). This finding loosely supports the notion that the managers of the winner HQ funds are more skilled as these funds perform best despite trading most often, but this is also consistent with trading costs declining in trade size. We can see that the HQ winner funds are on average the largest funds, which we expect should have the larger trades on average. Also, the winner funds tend to come from the largest families, which also suggests that trading costs might be lower for winner funds if dealers compete for family business. Moreover, fund and family size are nearly monotonically declining across the lagged-performance deciles. In short, we should control for fund and family size, as well as other characteristics, when examining persistence in performance. We do this in the next section.

Panel B of Table 9 shows that the relations between turnover, family size, and fund size with lagged performance are different for HY funds. None of these three characteristics are more extreme at the top or bottom of the deciles. The remaining columns in Table 9 provide means of maximum load and age. For both HQ and HY funds, the covariation in maximum load and age with lagged-performance is not particularly strong.

5.3 Regression evidence

To test for persistence in performance controlling for various fund characteristics, we employ the cross-sectional regression procedure used in Table 4, and described in section 4.2. Specifically, we examine how future 12-month performance relates to prior performance over months $[t-12, t-1]$ and months $[t-48, t-13]$, controlling for expenses, turnover, the existence of a load, and fund and family sizes. To measure performance over $[t-12, t-1]$, we use months $[t-24, t-1]$ to estimate the factor loadings.

We see first in Table 10 that the regression evidence of persistence in the performance of both HQ and HY funds echoes the (W-L) portfolio evidence in section 5.1. Across regression models, the coefficients on performance over the prior year ($\alpha_{t-12,t-1}$) and performance over the prior four years skipping last year ($\alpha_{t-48,t-13}$) are all positive, with all t-statistics above 2.10. The coefficients indicate that about 20% of prior abnormal performance is maintained, with the coefficients ranging from 0.149 to 0.35.[14]

The other variables that are strongly related to future performance in Table 4 without controlling for prior performance are now less important. The one variable whose explanatory power increases is last year's flow, $\text{Flow}_{t-12,t-1}$. Controlling for prior alpha reveals a negative relation between lagged flow and performance. This is presumably due to the cost of providing liquidity to fund investors (e.g., see Edelen (1999)).

We also estimate the cross sectional regressions in Table 10 using gross alphas. The point estimates and the t-statistics on the two lagged alphas, $\alpha_{t-12,t-1}$ and $\alpha_{t-48,t-13}$, are very close to those in Table 10, so we do not tabulate the gross-alpha results. In short, performance persists for at least four years after ranking, using either net or gross returns.

5.4 Stale Bond Prices

In the prior sections, we find that bond fund performance persists for at least four years. This is true for net and gross performance. A potential concern is the effect of stale bond prices. Corporate bonds are commonly viewed as less liquid than stocks

[14]These persistence magnitudes are roughly in line with the ratios of the performance spreads between winners and losers shown in Tables 5 and 6 to their corresponding ranking period spreads. The ranking period disparity across winner and loser alphas for the HQ funds is about 0.45% per month over the prior 12 months and 0.30% per month over the prior 48 months, and 1.10% and 0.60% for HY funds, respectively.

due to their less frequent trading. If a bond trades infrequently, its prices can be (spuriously) slow to incorporate new information. 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 most illiquid, nontraded securities, which they term "restricted," to maximize the long-term probability of exceeding a benchmark. For example, these funds report lower values for their restricted securities when their unrestricted securities perform either extremely well or extremely poorly, and they report higher values for their restricted securities when their unrestricted securities are performing just below their benchmarks.

In our setting however, it is important to remember that most of the persistence we are detecting lasts for years. Specifically, the performance of winners using gross returns and the spread between winners and losers using either net or gross returns persists for at least four years. Stale prices would seem to potentially generate only short-term effects, as the resolution of the staleness should rarely take more than a couple of months. However, the resolution of the staleness would be bond specific. That leaves open the possibility that a particular fund might be systematically trading the stalest of bonds over time. So at any moment, some bonds might have realized their price updates while others have not. The bottom line for our results on performance persistence is how often a given fund determines its net asset value using bond prices that deviate from those used to form the benchmark (Lehman) indices. To the extent that these prices are close or at least do not systematically deviate, fund performance should not systematically deviate from the benchmarks.

To examine whether staleness has any impact on our persistence findings, we add leads and lags on the factors in our factor models, as is commonly done to address stale pricing. We include leads to address the possibility that a given fund is updating its prices (to fair value) faster than the benchmark indices are updating. We replicate the analyses in Tables 5, 6, 7, and 8 in several ways to determine whether the alpha estimates from these prior tables are affected by adding leads and lags to the performance models. First, we rank funds over the prior 12 months based on the 2-factor model without leads and lags (using 24 months to estimate the loadings). Performances of the winners, losers, and the difference between the winners and losers over the following 48 months are examined using the 2-factor model with three leads and lags on the monthly factor realizations in addition to the contemporaneous ones. The results are very similar to those in the earlier tables. The net performance spread between the HQ winners and losers is 9 basis points per month over 48 months, with a t-statistic of 3.80 (similar to Table 5). The spread between HY winners and losers is 21 basis points per month, with a t-statistic of 3.63 (similar to Table 6). Ranking and evaluating based on gross alpha, we find the HQ spread to be 6 basis points per month over 48 months with a t-statistic of 2.60 (similar to Table 7), and the HY spread to be 17 basis points with a t-statistic of 3.46 (similar to Table 8). In addition, the gross alphas on the HQ winners are 8 basis points over the next 48 months with a t-statistic of 2.77 (similar to Table 7). In short, all of our prior findings pass through when controlling for systematic stale pricing.

Our second procedure to examine the effects of stale pricing is to replicate the above tests ranking on the style model (without leads and lags), but still evaluating with the 2-factor model using three lead and three lag terms. The findings are similar to those just noted. We also examine our models with only one lag, which might better accommodate a lower order moving average structure, if one truly exists. This third procedure replicates the above tests, ranking on the simple 2-factor model over 12 months, but employing just one set of lagged factors in the adjusted 2-factor model to evaluate future 48-month performance, using net returns only. The final procedure mimics the third but uses the simple style model to rank and the adjusted style model with one set of lags to evaluate future performance. For these last two tests, the HQ and HY point estimates and significance levels on the alphas of the winner, loser, and winner-minus-loser portfolios are, again, similar to the earlier tables.

5.5 No Return Momentum in the Underlying Corporate Bonds

Given how controlling for return momentum in stocks affects the evidence on performance persistence in stock funds (e.g., Carhart (1997)), it is perhaps useful to note that the returns of corporate bonds do not display momentum. Gebhardt, Hvidkjaer, and Swaminathan (2005) examine high-quality bond returns from 1973 to 1996 and find no evidence of momentum. Their data are provided by Lehman Brothers and are month-end bid prices. Lehman's trading of these bonds and their use of these prices to construct their widely followed indices suggests that the data are accurate. Using the Lehman data, we extend the finding of no momentum in corporate-bond returns through 2004 and to high-yield bonds. Our analysis is detailed in section A.3 of the Appendix.

6 Do flows chase past performance?

The performance of corporate bond funds persists for years. Our presumption is that the lack of diseconomies of scale in bond fund performance drives this result. In this section, we examine the related issue of the sensitivity of bond fund flows to past performance. Assuming that diseconomies of scale must exist at some threshold level of size, beyond the typical range of size at which current funds operate, we interpret the finding of performance persistence to indicate that fund investors do not chase past performance as much as they should. In this section, we examine whether investors chase past performance at all.

Sirri and Tufano (1998), Chevalier and Ellison (1997), Del Guercio and Tkac (2002) and others find that flows of assets under management at stock funds chase past performance, with the best-performing funds receiving the lion's share of the flow. We measure flow in month t as in equation 6, using monthly flows (instead of 12-month flows). To examine how flow relates to prior performance, we follow Sirri and Tufano's (1998) procedure and first determine in month t the percentile rankings of each fund based on performance according to the 2-factor model over $[t-12, t-1]$, with factor loadings estimated over $[t-24, t-1]$. We then estimate the following linear regression piecewise over quintiles of lagged performance. To do so, we form five quintile-based explanatory variables, Q1 to Q5. For $i = 1$ to 5

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

The coefficients on these measures captures the sensitivity of flow to prior performance within quintiles 1 to 5 respectively, with 1 as the lowest quintile. We also consider a vector of characteristics sampled at $t-1$ comprised of log(fund TNA), log(family TNA), 12b-1 fees, expenses minus 12b-1 fees (non12b-1), a load dummy, and lagged fund flow measured over $[t-12, t-1]$. The regression is estimated each month, and standard errors are estimated from the monthly time series of coefficients using Newey and West's (1987) procedure with six lags. Following Huang, Wei, and Yan (2006), we delete the top and the bottom 2.5% of the flow observations to remove extreme erroneous data on flows.

Table 11 shows the results of these regressions. For both HQ and HY funds, we see the convexity at the upper end of prior performance, which is a well-documented phenomenon in stock funds. The sensitivity of flows to lagged performance is at least three times greater in the top quintile than in the middle quintiles, and the coefficient in the top quintile is statistically different from zero. Interestingly, at the bottom-end of lagged performance, both HQ and HY flows also display strong sensitivity to performance. This result often does not appear in stock fund studies, but the convexity at the bottom end of stock fund performance is found by James and Karceski (2006) and Cashman, Deli, Nardari, and Villupuram (2007). However, even in these studies, the sensitivity of flow to past performance at the top end remains much stronger than the sensitivity at the bottom end. Table 11 displays similar coefficients for the top and bottom quintiles of bond funds.

To complement Table 11, we also calculate the mean flows for each lagged-performance quintile. Last year's HQ winners on average enjoy inflows of 1.07% per month, while last year's HQ losers suffer outflows of -0.34% per month. HY winners receive inflows of 1.74% per month on average, and HY losers suffer outflows of -0.48% per month. In short, flows of assets in corporate-bond funds are related to past performance, moving out of loser funds and into winner funds.

7 Conclusion

Corporate-bond mutual funds do not display diseconomies of scale, in contrast to the diseconomies that exist for stock mutual funds. One potential reason for this difference is that trading costs for bonds decrease with trade size while trading costs for stocks increase. Presuming that larger funds tend to make larger trades, large bond funds have a size advantage that large stock funds do not. Data on bond fund holdings, which are not readily available, may tell us more about this conjecture.

Regardless, the lack of any empirical relation between lagged fund size and fund performance has at least one important implication, according to Berk and Green (2004):

Bond fund performance should persist. Despite the fact that bond fund flows chase prior performance, winner bond funds do not suffer from the increase in size. This should allow winner bond funds to continue their good performances in the future, to the extent that their prior performance is based on skill.

We find that performance persists in corporate-bond funds for at least four years. This persistence is evident across winners and losers as well as in the positive alphas that winners generate before expenses are considered. Such long-lived persistence is unique to bond funds.

Our findings also offer a perspective on the stock fund literature. Berk and Green (2004) contend that diseconomies of scale and a competitive labor market for money management serve to erode persistence in fund performance. We find that without diseconomies of scale, fund performance persists. This finding seems to reinforce the contention that some stock fund managers are skilled yet performance persistence in stock funds is weak or even nonexistent.

The lack of diseconomies of scale in these bond funds is potentially important in other ways as well. One, assets under management in the mutual fund industry have increased dramatically over the last twenty years. The evidence of diseconomies of scale in stock funds indicates that investors should consider fund size, or expected size over future horizons, when selecting their stock funds. Our findings indicate that size considerations when choosing corporate-bond funds are currently unwarranted. Investors can seemingly gain by employing past performance to choose bond funds. Two, the lack of diseconomies of scale in bond funds better aligns the incentives of fund managers with their investors. Since compensation in this industry is largely based on the size of assets under management rather than performance, management's objective to increase the fund's size does not conflict with the investors' objective to maximize abnormal returns. Such a conflict seems to exist in stock funds.

A Appendix

We examine the performances of bond funds using the following models as well as the three detailed in section 2. Finding that these methods resulted in similar assessments of the average performance of bond funds, we chose to employ the three models in Section 2 going forward — to examine the relation between lagged fund size and performance and persistence in performance.

A.1 Alternative Performance Models

A.1.1 A Second Two-Factor Model

Our alternative two-factor 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.

$$R_t = \alpha + \beta_1 GC_t + \beta_2 HY_t + \epsilon_t \tag{7}$$

A.1.2 Six-Factor Model

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

- excess return on the CRSP value-weighted stock index (STK),
- excess return on the Lehman Aggregate bond index ($BOND$),
- return spread between the High-Yield index and the Intermediate Government index (DEF),
- return spread between the GNMA index and the Intermediate Government index ($OPTION$),

- change in the logarithm of the Composite Index of Leading Indicators (ILI)
- change in the logarithm of the Consumer Price Index (CPI, not seasonally adjusted, orthogonalized with respect to changes in ILI)

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

To estimate the return premium (price of risk) of each of the non-traded macroeconomic factors, we form a maximum-correlation portfolio, first introduced by Breeden, Gibbons, and Litzenberger (1989). We regress (orthogonalized) changes in each of the two macroeconomic factors on the returns to a basis set of seventeen assets, which are the Lehman Brothers Intermediate and Long indices for Aaa, Aa, A, Baa, Ba, B and Treasury bonds, the Intermediate Caa index, the 1-to-3-year Government index, and the Mortgage-Backed Securities index. The six-factor model then is

$$\begin{aligned} R_t &= \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_4 OPTION_t \\ &\quad + \beta_5 ILI_t^{MCP} + \beta_6 CPI_t^{MCP} + \epsilon_t \end{aligned} \tag{8}$$

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. However, these premia estimates are sensitive to the method used. For example, a cross-sectional regression approach provides a mean premium of -0.51%

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

for ILI and a mean premium of 0.10% for CPI. We only use the maximum-correlation estimates in our analyses.

A.1.3 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 accommodate 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

$$R_t = \alpha + \sum_k \beta_{kt} F_{kt} + \epsilon_t \tag{9}$$

where

$$\beta_{kt} = b_k^1 + b_k^2 Z_{t-1}. \tag{10}$$

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

$$R_t = \alpha + \sum_k b_k^1 F_{kt} + \sum_k b_k^2 \left(F_{kt} \otimes Z_{t-1}\right) + \epsilon_t. \tag{11}$$

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.1.4 Market-Timing Models

We examine the possibility 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 2-factor and style models in section 2 as well as the six-factor model above are extended to include a timing parameter as follows. In the Treynor-Mazuy case,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k F_{kt}^2 + \epsilon_t \tag{12}$$

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,

$$R_t = \alpha + \sum_k \beta_k F_{kt} + \sum_k \gamma_k \max(0, F_{kt}) + \epsilon_t \tag{13}$$

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

For both the Treynor-Mazuy and Henriksson-Merton timing parameters, the evidence of market timing is statistically weak and there is a tendency for the point estimates to be negative. For comparison, stock mutual funds display, if anything, this same tendency toward perversely negative market timing, as Ferson and Schadt (1996) for example find. Chen, Ferson, and Peters (2008) examine the timing abilities of fixed-income fund managers (excluding only money-market and municipal-bond funds) in great detail. After controlling for a myriad of potential issues such as convexity in bond returns, managers' conditioning on public information, stale pricing, and interim trading, they find a modest tendency at best for positive timing. In light of the inability of their improved tests to materially alter the conclusions on timing, we do not pursue further enhancements of the timing models. Note too that their performance metrics find that bond funds on average have negative alphas net of costs and positive alphas before costs. These findings are similar to ours, using simpler methods.

A.2 Evaluating Average Performance

Cornell and Green (1991), Blake, Elton, and Gruber (1993), and Elton, Gruber, and Blake (1995) conclude that bond funds generally underperform benchmarks net of expenses. However, none of these studies has a sample size of corporate-bond funds greater than one hundred or data later than 1991 (prior to the explosion in the number of funds shown in Table 1 and in capital invested). As just mentioned, Chen, Ferson, and Peters (2008) conduct a performance evaluation of bond funds taking into account potential market timing by funds and several other issues. Chen, Ferson, and Peters's

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

(2008) findings for average alpha before and after costs are similar to ours, which we provide below.

A.2.1 Net of expenses

We tabulate performances based on the 2-factor, 4-factor, and style models. Table A provides information on the distribution of alpha within high-quality and high-yield funds. As shown in Panel A, the mean and median performances of the HQ funds are negative, ranging from -0.06% to -0.02% per month across the three models. We employ an equally weighted portfolio (EW) of all available HQ funds each month to provide statistical inferences on the average fund's performance. The alpha for this calendar-time EW portfolio ranges from -0.05% to -0.03% and is statistically negative using the four-factor and the style models.

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

For those readers interested in the investors' experience in aggregate, the value-weighted alphas (not in the tables) for high-quality funds are two to three basis points per month greater than the equal-weighted alphas in Table A, reflecting the positive size effect shown in Table 3. The value-weighted alphas for high-yield funds, however, differ little from the equal-weighted alphas, consistent with the lack of a size effect in HY funds in Table 3.

A.2.2 Gross of expenses

Table B provides performance statistics of HQ funds gross of expenses, where annual expense ratios divided by 12 are added to net returns. We see that the mean and the median estimates of the gross alphas across funds are positive using the three performance models, ranging from 0.01% to 0.05% per month. The gross alphas for the EW portfolio of HQ funds range from 0.03% to 0.05% across the models with all three t-statistics greater than 2.60. In short, before fund expenses (but not transaction costs) are paid out, fund returns provide evidence that managers of HQ 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.

Table B also shows the performance of the HY funds gross of expenses is slightly less impressive. The mean and median alphas range from 0.04% to 0.10%; and the alpha estimates of the EW portfolio of HY funds ranges from 0.06% to 0.08%, but none are statistically significant. Part of this inability to reject the null hypothesis of zero alpha for the average HY fund seems due to a lack of power emanating from the greater volatility in HY bond returns.

A.3 No Return Momentum in Corporate Bonds

We examine monthly bond returns using data from Lehman Brothers, which are also used to construct their indices. 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 report 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. Below we evaluate the performances of these portfolios using the 2-factor model.

	(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-model alpha, and using only returns based on actual dealer quotes (instead of matrix prices) do not alter the findings.

In contrast, 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.

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Table 1. Summary Statistics of Annual Returns

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

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

Table 2. Characteristics of Corporate-Bond Funds

Over three subperiods and the full period (All), the means of fund characteristics and percentage holdings in certain asset classes are given for high-quality (HQ) and high-yield (HY) funds, in Panels A and B respectively. Age is length of time in years since first-offered date. Fund TNA is total net assets under management, in millions. Family TNA is cumulative TNA across all other bond funds in the same family, excluding the given fund, in millions. Turnover is the minimum of aggregate purchases of securities or aggregate sales of securities divided by the average TNA of the fund. Load is the sum of all maximum front, deferred, and redemption fees as a percentage of TNA. Expense ratios are from fiscal year-ends and are a percentage of TNA. The table also gives the mean percentages of fund investment in various asset classes. For each reported measure, we first average across funds each year and then average across years. Panels C and D give the pairwise correlations of the various characteristics, measured each year and then averaged across years, for HQ and HY funds respectively.

	Age	Fund TNA	Family TNA	Turn-over	Load	Exp. Ratio	Corp. Bonds	Govt. Bonds	Muni. Bonds	Conv. Bonds	Com. Stocks	Pref. Stocks	Cash	Other
Panel A : HQ Funds														
1990–1994	5.94	190	957	1.32	1.77	0.87	40.80	38.14	1.29	0.73	0.44	0.27	9.79	6.02
1995–1999	5.50	212	2690	1.70	1.49	0.95	41.64	38.45	0.62	0.77	0.42	0.40	6.67	9.87
2000–2004	7.01	308	6330	1.72	1.59	1.00	50.05	32.99	0.91	0.15	0.38	0.33	6.62	5.94
All	6.33	256	3325	1.67	1.58	0.96	45.94	35.56	0.85	0.44	0.40	0.35	7.01	7.36
Panel B : HY Funds														
1990–1994	9.06	351	1121	0.90	3.48	1.31	83.22	2.05	1.40	0.79	1.73	2.09	5.93	2.00
1995–1999	6.16	370	3184	1.10	2.72	1.35	84.22	1.66	0.01	1.66	1.44	3.32	4.98	1.53
2000–2004	6.93	258	5622	1.02	2.38	1.32	84.01	2.80	0.01	0.98	1.39	2.44	4.98	1.79
All	6.97	305	3309	1.03	2.63	1.33	84.01	2.36	0.14	1.18	1.44	2.69	5.06	1.73

Panel C: Correlations for HQ Funds

	Age	Exp. Ratio	Flow	Fund TNA	Family TNA	Load
Exp. Ratio	0.03					
Flow	-0.12	0.00				
Fund TNA	0.35	-0.29	-0.03			
Family TNA	0.10	-0.09	0.07	0.31		
Load	0.08	0.53	0.03	-0.22	-0.01	
Turnover	-0.02	0.05	0.01	0.01	0.02	-0.02

Panel D: Correlations for HY Funds						
	Age	Exp. Ratio	Flow	Fund TNA	Family TNA	Load
Exp. Ratio	-0.18					
Flow	-0.18	0.02				
Fund TNA	0.38	-0.29	-0.10			
Family TNA	0.01	-0.19	0.05	0.43		
Load	0.06	0.43	-0.08	0.21	0.10	
Turnover	-0.07	0.16	0.03	-0.22	-0.21	-0.06

Table 3. Relation between Next Year's Fund Performance and Size: Portfolio Tests

Each month we sort funds into quintiles based on the value of total net assets (TNA) at the end of the month. Following a calendar-time analysis, we calculate the equally weighted return in a given calendar month across the (up to) 12 portfolios that are in month 1, month 2, and month 12, respectively, in that calendar month. This produces a time series of monthly returns capturing fund performance across months 1 to 12. Mean monthly performance over the sample period is reported using raw returns and alphas from the 2-factor, 4-factor, and style models. Returns are in percent. The absolute value of the *t*-statistics are in parentheses, using standard errors estimated from Newey and West's (1987) procedure with six lags. Mean TNA for the funds in each quintile is also provided, in millions.

Size Quintile	Fund TNA	Raw Ret	2-factor α	4-factor α	Style α
Panel A: HQ Funds, Net Returns, Share Level					
1 (Large)	1187	0.58	0.00 (0.05)	-0.03 (2.44)	-0.02 (1.54)
2	162	0.54	-0.02 (0.69)	-0.05 (4.32)	-0.04 (3.37)
3	63	0.55	-0.01 (0.62)	-0.04 (3.39)	-0.04 (3.51)
4	25	0.53	-0.03 (1.26)	-0.06 (4.47)	-0.05 (4.37)
5 (Small)	6	0.51	-0.05 (2.38)	-0.08 (8.90)	-0.07 (9.30)
(1-5)		0.06 (6.00)	0.06 (5.55)	0.05 (5.24)	0.06 (5.56)
Panel B: HQ Funds, Gross Returns, Fund Level					
1 (Large)	1425	0.64	0.06 (2.39)	0.03 (2.24)	0.04 (2.96)
2	185	0.61	0.05 (2.19)	0.02 (2.42)	0.03 (2.34)
3	75	0.62	0.06 (2.38)	0.03 (2.83)	0.03 (3.15)
4	32	0.62	0.06 (2.29)	0.03 (2.41)	0.04 (3.18)
5 (Small)	9	0.61	0.04 (1.56)	0.01 (1.15)	0.02 (1.85)
(1-5)		0.03 (1.91)	0.03 (2.30)	0.02 (1.96)	0.03 (2.40)
Panel C: HY Funds, Net Returns, Share Level					
1 (Large)	1415	0.76	-0.06 (0.97)	-0.05 (0.74)	-0.04 (0.83)
2	346	0.79	-0.03 (0.59)	-0.01 (0.19)	-0.02 (0.66)
3	136	0.73	-0.08 (1.27)	-0.06 (0.98)	-0.06 (1.32)
4	43	0.75	-0.02 (0.46)	-0.02 (0.35)	0.00 (0.00)
5 (Small)	11	0.75	-0.02 (0.54)	-0.03 (0.60)	-0.01 (0.30)
(1-5)		0.01 (0.31)	-0.03 (1.05)	-0.02 (0.55)	-0.03 (0.96)
Panel D: HY Funds, Gross Returns, Fund Level					
1 (Large)	1513	0.85	0.02 (0.40)	0.05 (0.71)	0.04 (0.91)
2	377	0.90	0.09 (1.50)	0.11 (1.71)	0.10 (2.13)
3	148	0.81	0.00 (0.00)	0.02 (0.26)	0.02 (0.45)
4	51	0.87	0.09 (1.50)	0.10 (1.63)	0.12 (2.61)
5 (Small)	14	0.87	0.11 (2.12)	0.11 (2.43)	0.12 (2.95)
(1-5)		-0.01 (0.21)	-0.09 (2.33)	-0.06 (1.52)	-0.08 (2.60)

Table 4. Relation between Next Year's Fund Performance and Size: Regression Tests

Each month starting in January 1992, we examine whether fund size is related to net performance over months 1 to 12. We employ a calendar-time, cross-sectional method described in section 4.2. LoadDum is equal to one if a fund has a load, and 0 otherwise. Flow is defined in equation 6. The remaining variables are defined in Table 2. Performance is evaluated with either the 2-factor or style models. Coefficients on Turnover and Flow are multiplied by 100. The absolute value of the t-statistics (in parentheses) are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

	2-Factor Alphas		Style Alphas	
	HQ Funds	HY Funds	HQ Funds	HY Funds
lg(Fund TNA)	0.002	-0.004	0.001	-0.002
	(0.74)	(0.73)	(0.47)	(0.36)
ln(Family TNA)	0.002	0.005	0.004	-0.001
	(1.67)	(0.95)	(4.68)	(0.18)
Expenses	-0.854	-1.224	-1.017	-1.088
	(5.28)	(4.83)	(9.01)	(6.22)
LoadDum	-0.010	-0.019	-0.014	-0.025
	(2.22)	(0.73)	(3.31)	(1.18)
Turnover	0.006	0.001	0.004	0.001
	(2.39)	(0.08)	(2.06)	(0.06)
Age	-0.001	-0.002	-0.001	-0.002
	(2.16)	(1.43)	(2.97)	(1.65)
$\text{Flow}_{t-12,t-1}$	0.001	0.000	0.000	-0.003
	(0.66)	(0.01)	(0.51)	(0.41)
Intercept	0.045	0.116	0.001	0.097
	(1.56)	(1.76)	(0.06)	(1.82)
Adj R^2	0.07	0.05	0.07	0.05

Table 5. Persistence in Net Returns of High-Quality Funds

Each month staring in January 1992, we rank high-quality (HQ) funds based on prior performance net of expenses. The top decile are the Winners (W); the bottom decile are the Losers (L). We employ the calendar-time procedure described in section 5.1 to evaluate the funds over horizons greater than one month. The alphas net of expenses for the W portfolio over the future holding period, the L portfolio, and the Winners-minus-Losers (W-L) portfolio are given. Panel A ranks funds with the 2-factor model over the prior 12 months (left side of table) and the prior 48 months (right side of table). Panel B ranks funds with the style model. The holding-period alphas are based on the 2-factor, 4-factor, and style models for various holding periods: months 1 to 12, months 13 to 24, months 25 to 36, and months 37 to 48, respectively. The absolute value of the t-statistics are in parentheses and are calculated using Newey and West's (1987) procedure with six lags.

	Rank on Prior 12 Months						Rank on Prior 48 Months					
	2-Factor		4-Factor		Style		2-Factor		4-Factor		Style	
Panel A: Ranking with 2-Factor Model												
Hold over Months 1 to 12												
W	0.019	(0.67)	-0.016	(0.91)	-0.015	(0.80)	0.055	(1.73)	0.024	(1.09)	0.017	(0.82)
L	-0.089	(2.72)	-0.121	(5.71)	-0.104	(4.89)	-0.101	(2.73)	-0.151	(6.71)	-0.138	(6.08)
W-L	0.108	(3.83)	0.106	(3.73)	0.089	(3.18)	0.156	(4.69)	0.174	(5.33)	0.154	(4.51)
Hold over Months 13 to 24												
W	0.018	(0.55)	-0.021	(1.05)	-0.008	(0.41)	0.065	(1.92)	0.017	(0.71)	0.027	(1.17)
L	-0.064	(2.05)	-0.096	(4.71)	-0.106	(5.19)	-0.062	(1.65)	-0.130	(5.90)	-0.104	(4.68)
W-L	0.082	(2.66)	0.075	(2.43)	0.098	(3.04)	0.127	(3.96)	0.147	(4.49)	0.131	(3.87)
Hold over Months 25 to 36												
W	0.027	(0.76)	-0.007	(0.26)	-0.008	(0.32)	0.072	(2.21)	0.021	(1.00)	0.035	(1.40)
L	-0.075	(2.17)	-0.120	(5.93)	-0.109	(5.32)	-0.062	(1.59)	-0.120	(5.70)	-0.093	(4.71)
W-L	0.102	(3.03)	0.113	(3.32)	0.101	(2.87)	0.134	(3.99)	0.142	(4.24)	0.129	(4.19)
Hold over Months 37 to 48												
W	0.041	(1.16)	-0.008	(0.34)	0.004	(0.15)	0.055	(1.66)	-0.005	(0.20)	0.021	(0.70)
L	-0.053	(1.32)	-0.124	(4.88)	-0.092	(3.73)	-0.027	(0.62)	-0.094	(3.75)	-0.077	(3.53)
W-L	0.094	(2.49)	0.116	(3.02)	0.096	(2.45)	0.082	(2.03)	0.089	(2.29)	0.098	(2.70)
Panel B: Ranking with Style Model												
Hold over Months 1 to 12												
H	0.043	(1.69)	0.017	(1.06)	0.016	(0.93)	0.041	(1.51)	0.002	(0.10)	-0.003	(0.17)
L	-0.096	(3.12)	-0.131	(8.28)	-0.122	(7.69)	-0.085	(2.31)	-0.137	(6.63)	-0.122	(5.92)
H-L	0.138	(7.53)	0.147	(8.58)	0.138	(7.99)	0.126	(5.75)	0.138	(6.62)	0.119	(5.96)
Hold over Months 13 to 24												
W	0.013	(0.45)	-0.023	(1.36)	-0.023	(1.25)	0.070	(2.39)	0.012	(0.76)	0.024	(1.23)
L	-0.060	(1.91)	-0.097	(5.57)	-0.099	(5.97)	-0.068	(1.80)	-0.139	(6.81)	-0.108	(5.13)
W-L	0.073	(3.58)	0.074	(3.65)	0.076	(3.65)	0.138	(6.90)	0.152	(7.83)	0.132	(7.21)
Hold over Months 25 to 36												
W	0.010	(0.30)	-0.031	(1.30)	-0.035	(1.51)	0.081	(2.83)	0.033	(2.19)	0.045	(2.44)
L	-0.074	(2.15)	-0.119	(6.22)	-0.104	(5.56)	-0.082	(2.00)	-0.146	(6.93)	-0.105	(4.56)
W-L	0.085	(3.55)	0.088	(3.60)	0.069	(2.86)	0.163	(7.15)	0.179	(8.67)	0.150	(8.00)
Hold over Months 37 to 48												
W	0.062	(1.82)	0.005	(0.20)	0.013	(0.50)	0.071	(2.35)	0.011	(0.67)	0.025	(1.24)
L	-0.054	(1.40)	-0.129	(5.99)	-0.085	(3.76)	-0.052	(1.27)	-0.122	(5.64)	-0.095	(4.26)
W-L	0.116	(4.20)	0.134	(4.81)	0.097	(3.56)	0.123	(5.21)	0.133	(6.10)	0.120	(6.06)

Table 6. Persistence in Net Returns of High-Yield Funds

Each month staring in January 1992, we rank high-yield (HY) funds based on prior performance net of expenses. The top decile are the Winners (W); the bottom decile are the Losers (L). We employ the calendar-time procedure described in section 5.1 to evaluate the funds over horizons greater than one month. The alphas net of expenses for the W portfolio over the future holding period, the L portfolio, and the Winners-minus-Losers (W-L) portfolio are given. Panel A ranks funds with the 2-factor model over the prior 12 months (left side of table) and the prior 48 months (right side of table). Panel B ranks funds with the style model. The holding-period alphas are based on the 2-factor, 4-factor, and style models for various holding periods: months 1 to 12, months 13 to 24, months 25 to 36, and months 37 to 48, respectively. The absolute value of the t-statistics are in parentheses and are calculated using Newey and West's (1987) procedure with six lags.

	Rank on Prior 12 Months						Rank on Prior 48 Months					
	2-Factor		4-Factor		Style		2-Factor		4-Factor		Style	
Panel A: Ranking with 2-Factor Model												
Hold over Months 1 to 12												
W	0.060	(0.88)	0.062	(1.02)	0.085	(1.46)	-0.010	(0.15)	-0.028	(0.51)	0.030	(0.60)
L	-0.323	(4.42)	-0.313	(4.69)	-0.254	(4.02)	-0.282	(3.48)	-0.297	(3.82)	-0.183	(2.72)
W-L	0.383	(6.08)	0.375	(5.86)	0.339	(5.21)	0.272	(5.34)	0.269	(5.10)	0.213	(4.25)
Hold over Months 13 to 24												
W	-0.026	(0.36)	-0.038	(0.58)	0.040	(0.65)	0.011	(0.16)	-0.007	(0.14)	0.078	(1.72)
L	-0.194	(2.94)	-0.197	(3.22)	-0.126	(2.27)	-0.204	(2.44)	-0.240	(3.30)	-0.134	(1.94)
W-L	0.167	(3.45)	0.159	(3.25)	0.166	(3.25)	0.215	(4.20)	0.233	(4.41)	0.212	(3.84)
Hold over Months 25 to 36												
W	-0.084	(1.27)	-0.107	(2.09)	-0.047	(0.94)	0.019	(0.25)	0.007	(0.12)	0.063	(1.20)
L	-0.115	(1.62)	-0.146	(2.58)	-0.077	(1.42)	-0.156	(1.65)	-0.172	(2.16)	-0.108	(1.35)
W-L	0.031	(0.85)	0.039	(1.06)	0.030	(0.77)	0.175	(3.27)	0.179	(3.22)	0.171	(2.96)
Hold over Months 37 to 48												
W	0.019	(0.26)	-0.002	(0.03)	0.037	(0.66)	-0.013	(0.15)	-0.071	(1.08)	0.046	(0.71)
L	-0.093	(1.09)	-0.128	(1.78)	-0.028	(0.42)	-0.162	(1.57)	-0.209	(2.32)	-0.107	(1.18)
W-L	0.112	(1.89)	0.126	(2.03)	0.065	(1.06)	0.149	(2.42)	0.139	(2.15)	0.154	(2.28)
Panel B: Ranking with Style Model												
Hold over Months 1 to 12												
W	0.056	(0.84)	0.050	(0.88)	0.094	(1.71)	-0.039	(0.59)	-0.056	(0.99)	0.007	(0.13)
L	-0.259	(3.81)	-0.228	(3.51)	-0.199	(3.38)	-0.282	(3.61)	-0.291	(3.87)	-0.188	(2.88)
W-L	0.314	(5.86)	0.278	(5.10)	0.293	(5.18)	0.244	(4.96)	0.235	(4.67)	0.194	(3.95)
Hold over Months 13 to 24												
W	-0.045	(0.65)	-0.060	(0.98)	0.014	(0.24)	-0.019	(0.28)	-0.031	(0.55)	0.052	(1.10)
L	-0.177	(2.61)	-0.173	(2.77)	-0.105	(1.88)	-0.142	(1.90)	-0.166	(2.47)	-0.078	(1.28)
W-L	0.132	(2.96)	0.113	(2.52)	0.120	(2.55)	0.124	(2.78)	0.135	(2.94)	0.130	(2.71)
Hold over Months 25 to 36												
W	-0.076	(1.17)	-0.099	(1.95)	-0.041	(0.83)	0.016	(0.22)	0.008	(0.14)	0.061	(1.19)
L	-0.129	(1.93)	-0.149	(2.69)	-0.093	(1.75)	-0.117	(1.35)	-0.129	(1.76)	-0.070	(0.97)
W-L	0.054	(1.52)	0.051	(1.41)	0.052	(1.42)	0.134	(2.72)	0.137	(2.69)	0.131	(2.49)
Hold over Months 37 to 48												
W	0.007	(0.09)	-0.015	(0.28)	0.024	(0.46)	-0.036	(0.41)	-0.089	(1.32)	0.009	(0.14)
L	-0.149	(1.82)	-0.177	(2.48)	-0.064	(1.01)	-0.113	(1.15)	-0.170	(2.06)	-0.059	(0.71)
W-L	0.156	(2.76)	0.162	(2.74)	0.089	(1.58)	0.077	(1.35)	0.081	(1.36)	0.068	(1.09)

Table 7. Persistence in Gross Returns of High-Quality Funds

Each month staring in January 1992, we rank high-quality (HQ) funds based on prior performance gross of expenses. The top decile are the Winners (W); the bottom decile are the Losers (L). We employ the calendar-time procedure described in section 5.1 to evaluate the funds over horizons greater than one month. The alphas gross of expenses for the W portfolio over the future holding period, the L portfolio, and the Winners-minus-Losers (W-L) portfolio are given. Panel A ranks funds with the 2-factor model over the prior 12 months (left side of table) and the prior 48 months (right side of table). Panel B ranks funds with the style model. The holding-period alphas are based on the 2-factor, 4-factor, and style models for two holding periods: months 1 to 12 and months 13 to 48, respectively. The absolute value of the t-statistics are in parentheses and are calculated using Newey and West's (1987) procedure with six lags.

	Rank on Prior 12 Months						Rank on Prior 48 Months					
	2-Factor		4-Factor		Style		2-Factor		4-Factor		Style	
Panel A: Ranking with 2-Factor Model												
Hold over Months 1 to 12												
W	0.082	(2.63)	0.044	(2.34)	0.046	(2.24)	0.106	(3.13)	0.072	(3.14)	0.071	(3.31)
L	0.019	(0.58)	-0.013	(0.61)	0.003	(0.13)	0.016	(0.48)	-0.029	(1.32)	-0.020	(0.89)
W-L	0.063	(2.17)	0.057	(1.95)	0.043	(1.49)	0.090	(2.70)	0.101	(3.05)	0.091	(2.64)
Hold over Months 13 to 48												
W	0.082	(2.51)	0.045	(2.15)	0.057	(2.72)	0.121	(3.96)	0.073	(3.61)	0.090	(4.23)
L	0.039	(1.36)	0.006	(0.36)	0.003	(0.19)	0.060	(1.73)	0.000	(0.02)	0.017	(0.90)
W-L	0.043	(2.33)	0.039	(2.48)	0.053	(2.98)	0.061	(2.99)	0.072	(2.56)	0.073	(2.60)
Panel A: Ranking with Style Model												
Hold over Months 1 to 12												
W	0.103	(3.77)	0.074	(4.48)	0.079	(4.23)	0.092	(3.20)	0.055	(3.10)	0.052	(2.81)
L	0.014	(0.48)	-0.019	(1.27)	-0.013	(0.91)	0.033	(1.03)	-0.012	(0.69)	-0.005	(0.26)
W-L	0.089	(5.20)	0.093	(5.50)	0.092	(5.25)	0.059	(2.96)	0.068	(3.47)	0.057	(2.84)
Hold over Months 13 to 48												
W	0.087	(2.87)	0.051	(2.73)	0.049	(2.57)	0.128	(4.00)	0.078	(3.36)	0.088	(3.65)
L	0.040	(1.47)	0.004	(0.31)	0.008	(0.59)	0.045	(1.49)	-0.011	(0.74)	0.010	(0.68)
W-L	0.047	(2.97)	0.047	(2.96)	0.042	(2.53)	0.083	(3.98)	0.088	(4.12)	0.078	(3.62)

Table 8. Persistence in Gross Returns of High-Yield Funds

Each month staring in January 1992, we rank high-yield (HY) funds based on prior performance gross of expenses. The top decile are the Winners (W); the bottom decile are the Losers (L). We employ the calendar-time procedure described in section 5.1 to evaluate the funds over horizons greater than one month. The alphas gross of expenses for the W portfolio over the future holding period, the L portfolio, and the Winners-minus-Losers (W-L) portfolio are given. Panel A ranks funds with the 2-factor model over the prior 12 months (left side of table) and the prior 48 months (right side of table). Panel B ranks funds with the style model. The holding-period alphas are based on the 2-factor, 4-factor, and style models for two holding periods: months 1 to 12 and months 13 to 48, respectively. The absolute value of the t-statistics are in parentheses and are calculated using Newey and West's (1987) procedure with six lags.

	Rank on Prior 12 Months						Rank on Prior 48 Months					
	2-Factor		4-Factor		Style		2-Factor		4-Factor		Style	
Panel A: Ranking with 2-Factor Model												
Hold over Months 1 to 12												
W	0.147	(2.04)	0.147	(2.27)	0.175	(2.79)	0.060	(0.90)	0.048	(0.86)	0.101	(1.88)
L	-0.188	(2.67)	-0.173	(2.65)	-0.112	(1.89)	-0.167	(2.10)	-0.173	(2.23)	-0.071	(1.06)
W-L	0.334	(5.93)	0.320	(5.55)	0.287	(4.98)	0.227	(4.17)	0.221	(3.93)	0.172	(3.15)
Hold over Months 13 to 48												
W	0.077	(1.22)	0.071	(1.37)	0.122	(2.44)	0.126	(1.86)	0.107	(2.02)	0.171	(3.53)
L	-0.025	(0.42)	-0.034	(0.66)	0.027	(0.59)	-0.002	(0.03)	-0.034	(0.59)	0.046	(0.86)
W-L	0.102	(3.53)	0.105	(3.66)	0.095	(3.10)	0.128	(3.71)	0.141	(3.97)	0.125	(3.39)
Panel A: Ranking with Style Model												
Hold over Months 1 to 12												
W	0.119	(1.64)	0.108	(1.76)	0.165	(2.73)	0.025	(0.37)	0.013	(0.22)	0.074	(1.33)
L	-0.133	(1.95)	-0.101	(1.55)	-0.067	(1.14)	-0.187	(2.32)	-0.187	(2.33)	-0.085	(1.24)
W-L	0.251	(4.26)	0.210	(3.52)	0.231	(3.74)	0.212	(3.90)	0.200	(3.57)	0.159	(2.89)
Hold over Months 13 to 48												
W	0.075	(1.19)	0.068	(1.33)	0.115	(2.31)	0.117	(1.72)	0.106	(1.99)	0.162	(3.30)
L	-0.014	(0.23)	-0.013	(0.25)	0.040	(0.84)	0.005	(0.07)	-0.025	(0.43)	0.055	(1.03)
W-L	0.088	(3.19)	0.081	(2.86)	0.075	(2.61)	0.112	(3.08)	0.131	(3.56)	0.107	(2.74)

Table 9. Characteristics of Decile Portfolios Ranked on Prior 12-Month Performance

Each month t starting in January 1992, we rank funds based on net performance over the prior 12 months using the 2-factor model, with factor loadings estimated over the prior 24 months. The means of various characteristics, defined in Table 2, are calculated across funds within each decile and then averaged over time. Load and TNA are from month t. Turnover and expense ratios are from month $t+1$. The raw return, 2-factor performance (α), and the absolute value of the t-statistic for 2-factor performance are for month $t+1$. Panels A and B present the results for high-quality (HQ) and high-yield (HY) funds, respectively. The absolute value of the t-statistics are calculated using Newey and West's (1987) procedure with six lags.

Decile	Load	Age (Years)	Fund TNA (logs)	Family TNA (logs)	Exp. Ratio	Turn-over	Return_{t+1}	α_{t+1}	$\lvert t(\alpha_{t+1}=0)\rvert$
Panel A : HQ Funds									
1-Winner	1.24	8.84	4.72	7.04	0.07	2.06	0.58	0.04	1.30
2	1.19	9.49	4.71	7.01	0.06	1.61	0.52	0.02	0.76
3	1.26	9.01	4.59	7.04	0.06	1.78	0.51	0.01	0.33
4	1.35	8.52	4.45	6.91	0.07	1.58	0.51	0.00	0.00
5	1.47	8.42	4.32	6.76	0.07	1.67	0.49	-0.01	0.73
6	1.60	8.15	4.12	6.68	0.07	1.46	0.48	-0.03	1.38
7	1.80	8.35	3.99	6.67	0.08	1.38	0.48	-0.04	1.67
8	1.87	8.18	3.83	6.56	0.09	1.44	0.48	-0.04	1.59
9	2.15	8.35	3.64	6.56	0.09	1.49	0.47	-0.06	2.47
10-Loser	2.39	9.04	3.55	6.43	0.10	1.59	0.44	-0.13	3.33
Panel B : HY Funds									
1-Winner	2.60	10.71	4.97	6.82	0.10	1.16	0.81	0.17	2.52
2	3.06	10.56	4.94	6.95	0.10	1.08	0.72	0.07	1.28
3	3.18	10.33	4.98	7.18	0.10	1.04	0.70	0.05	0.81
4	3.26	9.97	4.98	7.10	0.10	0.99	0.64	-0.02	0.45
5	3.31	10.21	5.05	6.99	0.11	0.93	0.64	-0.02	0.42
6	3.20	10.08	5.05	6.97	0.10	0.92	0.61	-0.05	0.95
7	3.18	9.80	5.01	6.97	0.11	0.87	0.59	-0.08	1.63
8	3.17	9.44	5.02	7.08	0.11	0.95	0.56	-0.13	2.17
9	3.21	9.09	4.88	6.97	0.12	1.00	0.49	-0.20	3.11
10-Loser	3.08	9.72	4.46	6.63	0.12	1.15	0.29	-0.41	5.19

Table 10. Persistence in Fund Performance: Regression Tests

Each month starting in January 1992, we examine whether performance net of expenses over the prior 12 months and the prior 48 months excludng the first 12 months predict performance over months 1 to 12. We employ a calendar-time, cross-sectional method described in section 4.2. $\alpha_{[t-12,t-1]}$ is performance over months -12 to -1, and $\alpha_{[t-48,t-13]}$ over months -48 to -13. Performance is evaluated using either the two-factor or style model. Flow is defined in equation 6, and the other variables are defined in Table 2. Coefficients on Turnover and Flow are multiplied by 100. The absolute value of the t-statistics are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

	2-Factor Alphas		Style Alphas	
	HQ Funds	HY Funds	HQ Funds	HY Funds
$\alpha_{t-12,t-1}$	0.159	0.350	0.244	0.349
	(3.19)	(6.30)	(4.90)	(3.63)
$\alpha_{t-48,t-13}$	0.197	0.193	0.159	0.149
	(3.72)	(2.28)	(2.49)	(2.13)
ln(Fund TNA)	0.000	-0.001	0.000	0.002
	(0.23)	(0.13)	(0.23)	(0.40)
ln(Family TNA)	0.001	0.004	0.003	-0.002
	(0.86)	(0.64)	(2.48)	(0.27)
Expenses	-0.703	-0.356	-0.716	-0.256
	(3.52)	(1.48)	(4.82)	(0.92)
LoadDum	-0.004	-0.009	-0.009	-0.023
	(0.79)	(0.42)	(1.55)	(1.13)
Turnover	0.002	-0.002	0.002	-0.023
	(0.87)	(0.06)	(0.98)	(0.81)
Age	0.000	0.000	0.000	0.000
	(1.43)	(0.09)	(1.54)	(0.13)
$\text{Flow}_{t-12,t-1}$	-0.010	-0.064	-0.008	-0.048
	(2.16)	(2.53)	(2.32)	(2.05)
Intercept	0.049	0.012	0.002	0.013
	(1.88)	(0.17)	(0.18)	(0.23)
Adj R^2	0.16	0.11	0.15	0.13

Table 11. Regressions of Net Flow on Prior 12-Month Performance

Each month starting January 1992, we regress the cross section of net flow in month t (as a percentage of total net assets) on prior performance and other fund characteristics. We begin by ranking funds based on their 2-factor alphas over months $[t-12, t-1]$, assigning a percentile rank to each fund ($rank$). The factor loadings used to calculate the alphas are estimated over the prior 24 months. Following Sirri and Tufano (1998), we estimate the following linear regression piecewise over quintiles of lagged performance. Specifically, we define five variables (Q1 to Q5) based on percentile ranking of prior performance. For $i = 1$ to 5, $\mathrm{Q}i = \begin{cases} 0 & \text{if } rank < \frac{i-1}{5} \\ \min\left(rank - \frac{i-1}{5}, 0.20\right) & \text{if } rank \geq \frac{i-1}{5} \end{cases}$ The coefficients on these variables capture the sensitivity of flow to prior performance within quintiles 1 to 5 respectively. The characteristics sampled at month $t-1$ are monthly 12b-1 fees, monthly expenses less 12b-1 fees, load dummy, log(Fund TNA), log(Family TNA), and $\mathrm{Flow}_{t-12,t-1}$. We delete the top and the bottom 2.5% of the flow observations. These regressions are run for high-quality (HQ) and high-yield (HY) funds separately. The absolute value of the t-statistics are obtained from the monthly time-series standard errors of the coefficients and are calculated using Newey and West's (1987) procedure with six lags.

	HQ Funds	HY Funds
Intercept	-0.005	-0.006
	(1.92)	(1.58)
12b1fee	0.011	0.006
	(0.52)	(0.31)
Expenses (less 12b1)	-0.025	-0.011
	(1.72)	(0.54)
Loaddum	-0.001	0.001
	(1.06)	(0.94)
Ln(Family TNA)	0.000	0.001
	(2.49)	(2.42)
Ln(Fund TNA)	-0.001	-0.002
	(3.84)	(6.56)
$\mathrm{Flow}_{[t-12,t-1]}$	0.040	0.036
	(14.15)	(14.06)
G1 (Losers)	0.032	0.053
	(5.11)	(5.42)
G2	0.006	0.009
	(1.65)	(1.46)
G3	0.013	0.003
	(2.57)	(0.53)
G4	0.000	0.016
	(0.01)	(2.24)
G5 (Winners)	0.030	0.045
	(3.11)	(3.20)
Adj R^2	0.19	0.34

Appendix Table A. Average Net Performance

For funds with at least 24 months of returns, we estimate the mean monthly performance net of expenses (α) for each fund over its available months using the 2-factor, 4-factor, and style models from section 2. Panel A gives various statistics for the cross section of α for high-quality (HQ) and high-yield (HY) funds respectively, as well as the adjusted R^2 from the factor-model regressions. We also report the performance of the equally weighted portfolio (α_{EW}) of all available funds each month over the sample period 1990 to 2004. Panel B provides the Spearman rank correlations between the performance measures.

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

Panel B: Spearman Rank Correlation						
	HQ Funds			HY Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
2-Factor	1.00			1.00		
4-factor	0.85	1.00		0.95	1.00	
Style	0.82	0.83	1.00	0.87	0.86	1.00

Appendix Table B. Average Gross Performance

For funds with at least 24 months of returns, we estimate the mean monthly performance gross of expenses (α) for each fund over its available months using the 2-factor, 4-factor, and style models from section 2. Panel A gives various statistics for the cross section of α for high-quality (HQ) and high-yield HY) funds respectively, as well as the adjusted R^2 from the factor-model regressions. We also report the performance of the equally weighted portfolio (α_{EW}) of all available funds each month over the sample period 1990 to 2004. Panel B provides the Spearman rank correlations between the performance measures.

Panel A: Risk-Adjusted Performance

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

Panel B: Spearman Rank Correlation

	HQ Funds			HY Funds		
	2-Factor	4-Factor	Style	2-Factor	4-Factor	Style
2-Factor	1.00			1.00		
4-factor	0.81	1.00		0.94	1.00	
Style	0.80	0.79	1.00	0.87	0.87	1.00