Window Dressing in Bond Mutual Funds

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January 8, 2003

Abstract

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Key Words: Mutual Funds, Window Dressing, Portfolio Disclosure, Portfolio Composition, Securities Regulation

Acknowledgments: We thank Larry Harris, David Meyers, David Musto and seminar participants at the Securities and Exchange Commission and the 2002 Financial Management Association for very helpful comments on this paper.

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1. Introduction and Motivation

"We also are concerned about the misleading practice known as 'window dressing'. Here, advisers buy or sell portfolio securities at the end of a disclosure period for the purpose of misleading investors as to the securities held by the fund, the strategies engaged in by the advisers or the source of the fund's performance…We view this as an antifraud violation…We hope that funds have appropriate controls in place to prevent these abusive practices."

-Paul F. Roye, Director, Division of Investment Management, U.S. Securities & Exchange Commission[1]

Does window dressing occur in mutual fund portfolios? While the popular financial press contains anecdotal accounts of the practice, reliable evidence of its existence remains elusive. The typical window dressing scenario entails a fund manager replacing recent poor performing securities with top performers around the time of disclosure dates in an attempt to present to investors a portfolio loaded with high-quality names. The rationale for this behavior is that, in the face of previous poor fund performance, investors are more likely to stay the course if the underlying securities are recent high-fliers. Once the portfolio holdings have been disclosed, the fund manager reverses the cosmetic rebalancing, resulting in a significantly different investment vehicle than that presented to investors.

The detrimental effects of window dressing are two-fold. Most obviously, investors are misled about the sources of fund performance. Taken to the extreme, this deception could conceal investing behavior inconsistent with the fund prospectus. This implicit cost of cosmetic rebalancing is accompanied by a second detrimental effect of window dressing: additional explicit transactions costs borne to build and unwind cosmetic positions.

Despite the concerns voiced by the U.S. Securities and Exchange Commission, not a single case of window dressing has been brought by the Commission against a U.S. mutual fund. This lack of action is not surprising given the difficulty in identifying portfolio activities that are solely cosmetic in nature. The SEC currently requires mutual funds to disclose portfolio holdings twice a year. Absent voluntary disclosure, portfolio composition between disclosure periods is unavailable. Uncovering window dressing would therefore require the analysis of proprietary portfolio information on a case by case basis.

More frequent portfolio disclosure would likely reduce incentives to window dress; in the limit continual disclosure would render window dressing ineffective. However, fund advisors generally maintain that more frequent disclosure could limit their ability to profit on research analysis as the market is more quickly apprised of securities the manager feels are undervalued (perhaps before significant fund

[1] In a speech before the American Law Institute/American Bar Association Investment Company Regulation and Compliance Conference June 14, 2001, text available at: http://www.sec.gov/news/speech/spch500.htm.

positions can be built). Such costs to shareholders might outweigh the benefits of increased disclosure, and the SEC has recently declined to require more frequent disclosure by mutual funds.[2]

Despite the numerous news reports and SEC interest described above, rigorous academic studies of window dressing are quite sparse and often provide conflicting or insignificant results. For example, work on window dressing in equity portfolios has focused on the idea that managers will want to hold previous top-performing stocks in their portfolios at the time of disclosure to cosmetically improve their portfolio. However, the results of such studies indicate only weak evidence at best for such behavior. For instance, Lakonishok, Schleifer, Thaler, and Vishny (1991) uncover some evidence that pension funds window dress by selling more losers in the fourth quarter than at other times of the year. However, they fail to find corresponding increases in the purchases of winners that would be consistent with window dressing behavior. Other studies, such as Sias and Starks (1997) and Lee, Porter, and Weaver (1998), examine whether the January effect is caused by window dressing. While they do find evidence of window dressing, the behavior is primarily concentrated in stocks with greater individual rather than institutional ownership and hence suggests that institutional fund managers are not actively engaged in window dressing.[3]

Another area where window dressing behavior has been examined is in money market funds.[4] Unlike the equity fund studies that propose that fund managers window dress with winning stocks, the research here focuses on the notion that money market fund managers will window dress by holding safer securities at the time of disclosure. While the research in this area has found clearer evidence of window dressing than the equity fund work described above, the magnitude of such window dressing behavior may be so small as to render the effect economically insignificant. Musto (1999) examines the portfolio holdings of retail money market funds using a weekly newsletter that provides fund-specific information on money market fund holdings. These data include the percent of holdings allocated to Treasury securities, other government securities, commercial paper, and other money market categories. Consistent with the notion that managers will want to showcase a safer portfolio, he finds that retail

[2] For more on the potential costs of increased disclosure see Wermers (2001). Also see Frank, Poterba, Shackelford and Shoven (2002) for a study on the returns to strategies of copying disclosed mutual fund portfolios.

[3] Other papers that directly or indirectly examine equity fund window dressing include Haugen and Lakonishok (1988), Bremer and Kato (1996), Khorana (2001) and Poterba and Weisbenner (2001). Specifically, Haugen and Lakonishok are one of the first to theorize that the January effect is caused by window dressing, Bremer and Kato examine window dressing on the Tokyo Stock Exchange, Khorana investigates window dressing around mutual fund manager turnover, and Poterba and Weisbenner look at tax law changes and window dressing.

[4] The two major papers that examine window dressing in money market funds are Musto (1997, 1999).

money market funds tilt their allocation away from corporate securities and toward government securities around portfolio disclosures. These reallocations are more pronounced for funds with relatively poor previous-year performance. However, Musto concludes that funds reallocate on average only 0.3 percent of fund assets, an amount which may be immaterial.

The purpose of this paper is to use bond fund data to examine window dressing behavior such as that described in the money market fund case. Importantly, no study has directly examined window dressing using bond funds.[5] Given that bond funds constitute 36% of all non-money market assets invested in mutual funds, this large portion of the mutual fund market is worthy of examination.[6] More importantly, however, there are several aspects of the bond fund market and the data that we collect that make the subsequent examination more powerful and more interesting than that of previous studies of equity and money market funds:

1) *We can detect more subtle changes in bond fund portfolios than is possible with money market fund data.* Fundamentally, bond funds hold a wider range of securities than money market funds. Therefore the categories into which portfolio holdings can be grouped are more numerous, and this finer categorization will facilitate the detection of changes in portfolio quality. In our analysis we utilize a quarterly survey conducted by Morningstar that provides bond mutual fund portfolio credit quality holding data. These data allow us to examine the percent of bonds held in eight different bond quality grades at disclosure and non-disclosure periods. Such analysis differs from the work on money market funds which can only examine the percent allocations to government and non-government holdings.

2) *The effects of window dressing on investors are likely to be more pronounced in bond funds than in money market funds.* While bond funds typically hold securities with long term maturities, money market funds hold assets with short-term maturities.[7,8] As a result, money market fund managers can window dress without having to sell the initially held asset before it matures. While still misleading, such window dressing behavior does not result in

[5] There are several paper that have examined window dressing in regards to a January effect in bond yields, however the window dressing examination was only an ancillary aspect of the work. These papers include Chang and Pinegar (1986), Chang and Huang (1990), Maxwell (1998), and Fridson (2000).

[6] Investment Company Institute data, November, 2002.

[7] The average effective maturity of all corporate bond funds covered by Morningstar as of October, 2002 is 7.5 years.

[8] Money market funds may invest in longer-term securities, but they require demand features that permit funds to demand payment of the security at relatively short intervals.

increased transactions costs for investors. However, for bond funds, the transactions costs of window dressing are considerably higher as the manager will likely have to sell off the currently held bonds before they mature in order to buy the new assets. Such behavior obviously implies higher transactions costs from window dressing behavior. By looking at sample of bond funds, we are testing for window dressing that is both more deliberate on the part of the fund manager and more costly for fund investors.

3) *We are likely to see more window dressing behavior in bond funds than money market funds since bond fund investors typically hold their investments through several reporting periods.* Though some money market fund investors may hold for long periods, the wide use of these funds in retail sweep accounts and as institutional cash management instruments suggest short average holding periods. Conversely, bond funds are held for longer periods. As a result, it is reasonable to expect an investor in a bond fund to care more about the portfolio holdings than a money market fund investor.[9] If investors who hold through several reporting periods are more attuned to the holdings in the portfolio, there is greater impetus for fund managers with long term investors to window dress. As a result, a sample of bond funds may be a better class of funds to examine for window dressing behavior than money market funds.

In terms of our methodology, we examine the existence of window dressing in bond funds on two fronts using different datasets and methodologies. First, as described above, we utilize a quarterly survey conducted by Morningstar that provides bond mutual fund portfolio credit quality holding data. By analyzing these data we can not only test for the existence of window dressing but also the form the window dressing behavior takes. Our analysis of portfolio composition centers on the detection of differences in the credit quality exhibited in disclosure periods versus non-disclosure periods. To the extent that window dressing occurs, we assess whether bond fund managers are increasing quality or bolstering yields at disclosure.

To augment our credit quality holding analysis, we also examine daily return patterns of bond funds. Window dressing activities should cause fund returns around disclosure periods to be driven by a

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[9] This point is also substantiated by examining the costs of subscribing to data that would allow investors to monitor the portfolio holdings. The costs tell us, in some limited sense, how much demand there is for the information. Lower costs might indeed signify that there is more demand for such information. For retail money market funds, an annual subscription to the Money Fund Report (MFR) in 1999 would $1,195 (according to Musto (1999)). However, annual subscription to Morningstar' Principia program would have cost around $400.

different return-generating process than at other times of the year. To identify such behavior we investigate the loadings that funds have on components of a multiple-index market model. Our goal is to document whether funds appear to have different loadings on index components around disclosure periods than at other times of the year. Differences in factor loadings around disclosure periods indicate that the portfolio is temporarily tilted toward one sector of the bond market and away from another. Such differences are consistent with window dressing.

The rest of the paper is organized in three sections. Section 2 details the data, methodology and results of the portfolio credit quality holding analysis while section 3 treats the daily return analysis. We conclude in Section 4.

2. Portfolio Credit Quality Holdings Analysis

In this section we analyze the portfolio credit quality of a large sample of bond funds. Our data allow us to segregate our portfolio composition observations into those periods in which the fund has an official SEC reporting period and those that do not. Differences in reporting and non-reporting period holdings are then examined in several ways to uncover systematic portfolio composition changes that may be consistent with window dressing.

2.1. Portfolio Credit Quality Holdings Data

2.1.a. The Morningstar Data

The portfolio credit quality holding data are drawn from the Morningstar quarterly data disks. The holdings data are acquired by Morningstar through a quarterly survey that Morningstar itself distributes directly to the funds, where the quarterly dates are the end of March, June, September and December.

The holdings data provided by Morningstar are not the actual bonds held by the fund. Instead, Morningstar provides a credit quality analysis for each fund. The credit quality analysis shows the percentage of bonds held by the fund in various credit quality grades. These grades are U.S. Government, AAA, AA, A, BBB, BB, B, Below B, and NR/NA, where bonds listed as grades BB or below are non-investment grade.[10] Along with the credit quality breakdown Morningstar also provides the date of the credit analysis data for each fund.

The fact that the data are based on a survey raises several issues. First, the frequency and the consistency of the disclosure of the data are not constant. While a vast majority of the bond funds report the credit analysis data once or twice a year, a small minority report every quarter (four times a year) and

[10] Even though Standard and Poor's and Moody's both classify U.S. Government Bonds as AAA-rated, Morningstar separates out these funds from AAA-rated securities in the credit analysis to allow for a more accurate picture of a fund's holdings.

an even smaller minority only report once every couple of years. Therefore we do not have data for each quarter for every bond fund. Nevertheless we are exhaustive in our use of the Morningstar data using every unique data point that we can find in our sample range.

Second, there is no way to verify whether the information provided to Morningstar by the funds is accurate. Indeed, one might expect to find no window dressing behavior in this sample as the funds may report holdings information to Morningstar that only shows them in a positive light. As such, our use of these data should provide a conservative test of the existence of window dressing in our sample since reporting selection bias may be an issue.[11]

2.1.b. Collection of the Data

Our objective in collecting the data was to include as many observations points as possible. However, due to the fact that the credit analysis data are not consistently updated, we collected the data in the following manner. First, we used 13 quarterly Morningstar data disks (March 1998-March 2001). We chose this period as we had access to these disks and because the gathering of these data from the disks is extremely onerous.[12] For each disk we then selected all corporate bond funds. Morningstar subdivides this category into corporate-bond-general funds and corporate-bond-high-quality funds.[13] Then for each fund from each disk we obtained the credit analysis information. This procedure produced just over 9,000 credit analysis data points.

We then narrowed our sample of credit analysis data points in the following five ways:

1) For each disk of data, we eliminated all replicate credit analysis data points that were caused by multiple share classes. We did this to avoid a fund being counted more than once per disk.
2) We eliminated all credit analysis data points which were listed on earlier disks. For example, since many funds only update their credit analysis data once or twice a year, the same credit

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[11] We examined many other data providers in an attempt to find bond portfolio holding data. To our knowledge no other major data provider has any data on bond fund holdings.

[12] Specifically the difficulty was in eliminating the replicate and overlapping data points. For the replicate funds we had to identify each multiple class fund and individually delete it from each of the 12 Morningstar data disks. For the overlapping funds we had to examine the credit quality holding data of each fund quarter by quarter and then delete any data points that were the same as the previous time period. That is, we had to follow each fund and find if the credit analysis information was the same as before or was updated and then delete any overlapping data points. Moreover, following the funds meant following the funds through name changes.

[13] Morningstar defines High Quality funds as those that invest at least 65% of their assets in securities rated A or better. General funds may hold a variety of debt securities with no specific thresholds for quality or yield.

analysis data could appear on two or three consecutive disks. To avoid counting the same data points more than once we eliminated these overlapping data points.

3) We eliminated any credit analysis data points that contained missing data.
4) We eliminated all credit analysis data points for funds that did not have a fiscal year-end provided by Morningstar.
5) We eliminated all credit analysis data points from index funds. Index funds are constrained in their holdings by the index and hence are not likely to engage in window dressing.

After these adjustments, the sample consisted of every unique non-index, corporate bond credit analysis data point that existed on the March 1998 to March 2001 Morningstar disks that had fiscal year-end information. This procedure yielded 3,170 credit analysis data points.[14]

2.1.c. Disclosure/Non-Disclosure Data points

The next step in analysis is to define each of the 3,170 credit analysis data points as a disclosure or non-disclosure data point. A disclosure data point is one where the date of the credit analysis data coincides with the fiscal year-end or half-fiscal year of the fund. All other credit analysis data points are non-disclosure data points. For example, consider a fund with a credit analysis data point of 12/31/98. If the fund had a fiscal year-end of December or June, then that credit analysis data point would have been considered a disclosure data point. If the fund had any other fiscal year-end, the credit analysis data point would have been considered a non-disclosure data point.

In our sample we found 804 disclosure data points which represent 25 percent of the sample. Since the disks provide quarterly updates of the credit quality analysis, all but nine of the disclosure observations take place at the month ends of March, June, September and December, with the data points being spread relatively evenly among the four quarters. More specifically, December had the most observations with 259 followed by June (247), March (148) and September (141). For the non-disclosure data points there were a total of 2,366 data points with December again having the most with 643 followed by March (567), June (524), September (524) and 108 data points that were not on the quarter end.[15]

[14] The vast majority of the excluded data points came from excluding the replicate and overlapping data points (points 1 and 2).

[15] There were a limited number of data points where the credit analysis data were not given on a quarter end. We included these observations to be as inclusive as possible. However, the vast majority of the disclosure (99 percent—795 of 804) and non-disclosure (96 percent—2258 of 2366) data points were on quarter ends. We adjust for the inclusion of these data by including a dummy variable for observations not on the quarter end.

2.2.a. Methodology of the Portfolio Credit Quality Holding Analysis

Using the data described above we tested to see if the quality of the bond holdings differed between disclosure and nondisclosure periods while controlling for differences in time and style of funds. For this portion of the analysis, we estimated the following equation:

$$\begin{aligned} QualityHeld_i &= \alpha_0 + \beta_1 (June)_i + \beta_2 (September)_i + \beta_3 (December)_i \\ &+ \beta_4 (NonQuartend)_i + \beta_5 (1997)_i + \beta_6 (1998)_i + \beta_7 (1999)_i + \beta_8 (GeneralStyle)_i \\ &+ \beta_9 (Disclosure)_i + u_i \end{aligned} \quad (1)$$

where,

$QualityHeld_i$ =	Amount of bonds held in a bond quality category (expressed as a percentage of the entire fund's bond holdings),
June =	A dummy variable coded 1 if the credit analysis data point came at the end of June, 0 otherwise,
September =	A dummy variable coded 1 if the credit analysis data point came at the end of September, 0 otherwise,
December =	A dummy variable coded 1 if the credit analysis data point came at the end of December, 0 otherwise,
NonQuartend=	A dummy variable coded 1 if the credit analysis data point came on a non-quarter end, i.e. not the end of March, June, September or December, 0 if it did come on a quarter end,
1997 =	A dummy variable coded 1 if the credit analysis data point came in 1997, 0 otherwise,
1998 =	A dummy variable coded 1 if the credit analysis data point came in 1998, 0 otherwise,
1999 =	A dummy variable coded 1 if the credit analysis data point came in 1999, 0 otherwise,
GeneralStyle =	A dummy variable coded 1 if the credit analysis data point was a corporate bond general fund, 0 otherwise,
Disclosure =	A dummy variable coded 1 if the credit analysis data point is a disclosure datapoint, 0 if a non-disclosure data point,
i =	1 through *N*, where *N* is the total number of credit analysis data points in the sample.

The reference group for equation (1) consists of the March, 2000, corporate high-quality, non-disclosure credit analysis data points.

2.2.b. Bond Quality Held Measures

For equation (1) we used 15 separate bond quality held measures (the dependent variable). Nine of these were the percentage of bonds held in the following categories: Government, AAA, AA, A, BBB, BB, B, Below B and NA/NR. Two were the percentage held in investment grade corporate bonds (the percent held in categories in AAA-BBB grades) and the percentage held in non-investment grade corporate bonds (the percent held in categories BB to below B). The five others were the following measures of aggregate bond quality:

1) *The Morningstar Average Credit Quality Measure.* Morningstar calculates this measure based on the credit analysis data and assigns an average quality that ranges from AAA to Below B. All the data points in our sample had Morningstar average credit quality measures that ranged from AAA to BB. To quantify these average credit quality ratings we gave scores of 5 to 1, where AAA received 5, AA received 4, A received 3, BBB received 2 and BB received 1.[16]

2) *Method 1.* This measure involved using a linear weighting scale of 8 to 1 where government bonds received a weighting of 8, AAA-rated bonds received a weighting 7, AA-rated bonds received a weighting of 6, A-rated bonds received a weighting of 5, BBB-rated bonds received a weighting of 4, BB-rated bonds received a weighting of 3, B-rated bonds received a weighting of 2, less than B-rated bonds received a weighting of 1, and NA/NR-rated bonds received the average weighting of 4.5. This method insured that Government bonds were treated slightly differently than AAA-rated corporate bonds and that the NA/NR rated bonds are treated as having an average weighting rather than no rating.

3) *Method 2*. Method 2 was the same as Method 1 with the NA/NR rated bonds receiving a weight of 0.

4) *Method 3.* Method 3 was similar to Method 1 except that we weighted Government and AAA-rated bonds equally. NA/NR-rated bonds again received the average rating in this method.

5) *Method 4*. Finally, Method 4 was the same as Method 3 with NA/NR rated bonds receiving a weight of 0.

2.3. Results

The results of the estimation of equation (1) are presented in Tables 1-4. Table 1 shows the results using four bond quality held measures: the percentage of bonds held in government bonds, investment grade corporate bonds (AAA-BBB rated), non-investment grade corporate bonds (BB-Below B rated), and unrated bonds (NA/NR). The table shows the results for three different samples: the full sample, the sample of corporate general bond funds, and the sample of corporate high-quality bond funds. Tables 2-4 detail the results using the nine different bond grades and the five aggregate measures of bond quality. Table 2 presents results on the full sample while Tables 3 and 4 present results for the general and high-quality samples respectively. We concentrate our initial discussion below on the results in Table 1.

[16] Note that for a few observations Morningstar did not provide the average credit rating data. Hence the sample for this analysis is slightly less than the others. Of the 3170 credit analysis data points, 3127 had the Morningstar average credit quality rating measure.

Table 1 documents several interesting findings. First and most important, funds hold significantly more government bonds during disclosure than non-disclosure. For the full sample we find that funds allocate 3.5 percent more to government bonds during disclosure periods than non-disclosure periods. This result supports the notion that bond funds window dress their funds at disclosure by adding safe government bonds to their portfolios and dumping other types of bonds. Such behavior is consistent with Musto's (1999) finding that retail money market funds tilt their allocation away from corporate securities and toward government securities around portfolio disclosures. Consistent with intuition, we find that the increase in government holdings is stronger for high-quality funds (~5%) than general funds (~2.7%).

The second interesting finding is that along with the increase in government bond holdings during disclosure, we also find evidence that, on average, funds are holding more non-investment grade corporate bonds during disclosure. This evidence is documented for both the full sample and the general style sample (although only at the 10 percent level in the general sample). Although this evidence is weaker than that for the increase in government bond exposure, it is confirmed in our examination of finer categorizations of bond grades. The percentage of bonds held in the BB category during disclosure is significantly higher at the 10 percent level as shown in Table 2 (full sample) and Table 4 (corporate general sample). These findings suggest that some funds may add to non-investment grade holdings at disclosure periods to increase reported yields. That is, similar to equity funds holding recent high performing stocks, these funds may rebalance to hold high yielding bonds to make their funds look more attractive.

Third, our results indicate that exposure to investment grade corporate debt is reduced during disclosure. This result holds for the full sample and the two subsamples, and the reductions in corporate holdings are significant at the 1% level. In Tables 2-4 we see that the decrease in investment grade bonds is largely caused by the large decreases in AAA grade holdings during disclosure.

Fourth, the aggregate measures of bond quality on the right hand sides of Tables 2-4 are not affected by disclosure/nondisclosure for the full sample and the general style sample. For these samples, the increase in quality caused by the rise in the government bond holdings is apparently negated by the increase in non-investment grade bonds. Only in the high-quality sample do we see that the overall quality of the bonds holdings is significantly increased (see the results of Aggregate Methods 1, 2 and 4). Intuitively this result is appealing since any window dressing at high-quality funds is most likely to consist of moves toward higher quality than moves toward higher yield.

In summary, the results of Tables 1-4 indicate that two types of window dressing are being practiced. We find clear evidence that funds in aggregate are holding more government bond funds during disclosure and so increase their quality of holdings. We also find, to a lesser extent, evidence that funds are holding more non-investment grade bonds in a possible attempt to increase their reported yield.

Furthermore, the bonds that are sacrificed during disclosure are investment grade corporates. Finally, we find that the move towards government bonds is stronger in high-quality bond funds than in general quality funds.

2.4. Robustness Checks of Portfolio Credit Quality Holding Results

We performed several tests to examine the robustness of our stated results in Tables 1-4. The following subsection describes these tests and the results of our findings.

2.4.a. Fixed Effects

In addition to equation (1) we also ran a fixed effects model where all quarters (except a reference quarter group) were represented by dummy variables. That is, rather than just using the June, September, December and annual dummies, every single quarter was represented by a dummy variable. Moreover, as in equation (1) the non-quarter ends data points were similarly represented by their own dummy variable. The results of this analysis were qualitatively the same as those shown in Tables 1-4. These results are available upon request.

2.4.b. Yields and Credit Spreads

The adjusted R-squared values in Tables 1-4, particularly in the high-quality sample, were so low as to cause concern that we had mis-specified the model. To try to combat this problem, we used quarterly yields and credit spreads as additional explanatory variables in equation (1). We used the Treasury yield, corporate yield spread separately and together in the regressions and found that the results were again very similar to those in Tables 1-4. Furthermore the variables added little explanatory power and were not significant themselves as control variables.

2.4.c. Breaking the Sample Into Separate Groups

As a traditional robustness check we spilt the sample into two subgroups (sample 1-1585 and sample 1586-3170) and re-estimated equation (1). Again the results were very consistent with those reported in Tables 1-4.

2.4.d. Exclusion of Non-Quarter End Data Points

As yet another robustness check we eliminated the 117 non-quarter end data points from our sample (9 disclosure and an 108 non-disclosure) and re-estimated equation (1). Again, we found the results to be qualitatively similar to those reported in Tables 3-4.

2.4.e. Credit Analysis Pairs Test

As another robustness check, we examined whether window dressing was evident by tracing a specific fund's credit analysis data points over time. The basic idea was to find a fund's credit analysis on a disclosure date and then pair that data point with the fund's quarterly adjacent non-disclosure credit analysis data point. By having disclosure and non-disclosure data points that were just one quarter apart we could examine if our results reported in Tables 1-4 generally held as we examined funds over time. This section describes this analysis.

As mentioned in section 2.1.a., the portfolio credit quality holding data from Morningstar is not updated every quarter for every fund. Some funds update once a year while others update more or less frequently. In light of these data difficulties we were forced to use a relatively complex method of acquiring data for this robustness check and were able to examine less than half of the 3,170 credit analysis data points mentioned in sections 2.1-2.4.d.

For this test we gathered the data in a slightly different manner than the previous tests. For each Morningstar data disk from March 1998 to December 2000 (12 total disks) we collected all corporate bond funds (both general and high-quality) that had fiscal year-ends of March, June, September and December. Our rationale for choosing these funds was that Morningstar's portfolio composition surveys are conducted on a quarterly basis (March, June, September, and December). As a result, by selecting funds with these fiscal year-ends we were likely to have the composition data on disclosure dates *and* on non-disclosure dates. For other funds, the composition data would always occur on non-disclosure dates.

After narrowing the sample down by selecting funds with these fiscal year-ends, we then reduced the sample even more by excluding funds that were simply replicates of other funds in the sample, i.e., class B, C shares, etc. Also, if a fund did not have credit analysis data, it was eliminated.

Finally, with the resulting sample of funds, we examined each fund to see if it survived to the next quarter by examining the next quarter's disk. So for the March 1998 sample we examined the June 1998 disk. If we found that the fund had survived, we then evaluated whether the fund's credit analysis data had been updated for the next quarter.[17] If we found that the credit analysis data had been updated, then the credit analysis data found from the earlier disk and the credit analysis data taken from the later disk were put together to form a "credit analysis pair". Since the credit analysis data are updated by Morningstar on a quarterly basis and because we examined funds with fiscal year-ends of March, June,

[17] Note that since the disks are only one quarter apart, the vast majority of funds survive from one disk to the other. It should be noted, however, that there were a significant number of funds that changed their name from one quarter to the another. We made every attempt to include all funds that survived regardless of whether their names changed between quarters or not.

September and December, each "credit analysis pair" was composed of a fund's credit analysis data on a disclosure date and on an adjacent non-disclosure date.

To better understand this complicated data extraction process consider an example. The Calvert Income A Fund was a fund that met our criterion on the March 1998 disk. The fund was classified as Corporate Bond—General fund and had a fiscal year-end of September, meaning that it disclosed its portfolio holdings to the SEC at the end of September and March. On the March 1998 disk, this fund had credit analysis data dated 12-31-97 (typically the credit quality holding information lags the data disk by one quarter). Using the June 1998 disk we found that the fund had survived to the next quarter *and* had credit analysis data listed for next quarter, dated 3-31-98. Since the Calvert Income A had a September fiscal year-end, the 12-31-97 credit analysis data point constituted a non-disclosure date, and the 3-31-98 credit analysis data point represented a disclosure date. Hence, taken together, these two credit analysis data points made up a credit analysis pair.[18]

The results of the tests are presented in Table 5. The table shows 24 different samples of credit analysis pairs. We show 12 samples where the disclosure data point follows the non-disclosure data point and 12 samples where the disclosure data point precedes the non-disclosure data point. We organize the results in these 24 samples so as to control for time, i.e., a fund may have decided to alter the quality of its holdings not because the period was a disclosure period or not, but rather due to the overall market conditions at the time. By simply aggregating the 24 samples into one we lose any ability to control for these effects.

In the table we show the average difference between the disclosure percent holdings and the non-disclosure percent holdings for each sample of credit analysis pairs. That is, we simply subtract the holdings of the non-disclosure data point from the percentage holdings of the disclosure data point for each credit analysis pair and take the average for all the credit analysis pairs in the particular sample. We

[18] Note that after identifying all the credit analysis pairs in the Morningstar disks, we then narrowed the sample of credit analysis pairs in four ways. First, we excluded credit analysis pairs for which the fund merged into another fund between quarters. Our rationale for eliminating these pairs was that changes in these funds composition data could be due to the merger and not the result of window dressing. Second, we excluded credit analysis pairs that had data points whose holdings did not add up to 100 percent. As stated before, Morningstar's credit analysis data show the percentage of fixed-income securities that fall within each credit quality rating as assigned by Standard and Poor's or Moody's. Moreover, they show the percentage of funds that are not rated or not available to be rated. These percentages should add up to 100 percent; however, in a very few cases they differ substantially from 100 percent. Since our tests of window dressing are based on the changes in the composition of the fund between the disclosure and non-disclosure periods, such deviations could obviously lead to misleading results and as a result these pairs were eliminated. Third, we excluded all credit analysis pairs of index funds (consistent with our previous analysis). Fourth, we excluded any credit analysis pair in which the credit analysis data points were not exactly one quarter apart or did not fall on the exact quarter ends. We did this to insure that our test is sensitive to the time of the credit analysis report.

use four quality categories: Government, Investment Grade Corporates (AAA-BBB rated), Non-Investment Grade Corporates (BB-Below B rated), and unrated bonds (NA/NR). Again, the non-disclosure percentage holdings are always subtracted from the disclosure percentage holdings so the positive (negative) numbers always indicate that the percentage of bonds held were higher (lower) during the disclosure period than the non-disclosure period.

Due to the lack of data, for some of the 24 samples there are only a few credit analysis pairs. Hence, it is difficult to identify many statistically significant findings in the Table. However, the signs on the average differences do give us some limited support for the results reported in Tables 1-4. We find that in a majority of the samples more government and more non-investment grade bonds are held at disclosure. We also find that in a majority of the samples fewer investment grade bonds are held at disclosure. Specifically, we find that in 15 of the 24 samples more government bonds are held, in 16 samples more non-investment grade bonds are held, and in 14 of the samples less investment grade corporate bonds are held.

2.4.f. A Stronger Test for Calendar Effects

As a final robustness check we performed a test using a methodology very similar to Musto (1999) that more thoroughly controls for calendar effects. We examine the averages of the credit analysis pairs reported in Table 5 in a different way. To better understand this test consider the following example.

The first group (group 1—we organize them as groups here for ease of exposition) on Table 5 shows the disclosure minus non-disclosure average holdings for funds that reported portfolio holding information to Morningstar on December 31, 1997 and on March 31, 1998. For this group, March 31, 1998 represents the disclosure date and December 31, 1997 represents the non-disclosure date. Conversely, group 13 on Table 5 shows the results for funds that report at the same time but the disclosure date is December 31, 1997 and the non-disclosure date is March 31, 1998. For the current test, rather than calculate the holdings at disclosure minus the holdings at non-disclosure as we have done in Tables 1-5, we instead subtract the holdings at the end of the quarter from the holdings at the beginning of the quarter. For group 1 this produces the same results as in Table 5 as the disclosure date came after the non-disclosure date. For group 13 the results now have the opposite sign as compared to Table 5 as the disclosure date is at the beginning of the quarter.

The results of this analysis are indicated on top part of Table 6. They show that for group 1 the holdings of government bond increased by 1.27 percent from the beginning of the quarter while for group 13 the holdings of government bonds increased by 0.755 percent from the beginning of the quarter. Thus the results for group 1 indicate a movement toward government bonds at disclosure. Conversely, the findings for group 13 show a movement towards government bonds at *non-disclosure*.

We then calculate the difference between holding averages of group 1 and group 13. The resulting number gives us a sense of the movement towards certain bond holdings while more thoroughly controlling for calendar effects. For instance, the difference between the two averages of group 1 and 13 for government bonds is 0.515 indicating that even after controlling for calendar effects there is some evidence of funds holding more government bonds at disclosure. If instead the number had been negative it would indicate that funds are holding less government bonds at disclosure.

Table 6 presents the full results of this analysis. The first two groups examined are pair 1 and 13 as described above, however we examine the differences of all 12 sets and then calculate the average of all 12 differences. The results at the bottom of Table 6 show similar results to the previous results in Tables 1-5. We find that funds at disclosure are holding more government bonds and non-investment grade bonds and less investment grade bonds. It should be noted that the averages of the 12 cases are not significant at traditional levels in the government bond cases and yet are significant in the investment grade (at the 10 percent level) and non-investment grade (at the 5 percent level) cases.

3. Daily Return Analysis

There are two difficulties we face in attempting to uncover window dressing in our data. First, it is likely that only a subset of fund managers practice window dressing. Therefore the effects that we attempt to detect by analyzing average holdings across the sample of all bond funds are diluted. If only 1 in 10 fund mangers is window dressing, the effect in our sample will be only one tenth as strong as the actual rebalancing occurring in the single window-dressed portfolio. Second, our results suggest that two types of window dressing exist. One increases quality while the other increases yield. Unfortunately, these two forms of window dressing will offset each other in terms of overall portfolio credit quality. We see this effect in the insignificant results with aggregate bond quality measures in tables 2 and 3.

In this section of the paper, we examine the daily return patterns of funds to detect changes in the return-generating process consistent with window dressing. We perform this analysis on a fund-by-fund basis and, because we have many daily observations per fund, can, with some degree of statistical reliability, detect window-dressing in certain funds in the sample. This analysis also allows us to observe the direction of window dressing in the funds in the sample without the offsetting effects we face when studying portfolio weights in the cross-section of our sample.

Essentially, we investigate the loadings that funds have on components of a dual-index market model. Our goal is to document whether funds appear to have different loadings on index components around disclosure periods than at other times of the year. Differences in factor loadings around disclosure periods indicate that the portfolio is tilted toward one sector of the bond market and away from another. Such differences are consistent with window dressing.

3.1. Data Collection

Data for the daily return analysis comes from two sources: Morningstar and DialData. From the Morningstar Principia Pro Plus database of September 2001 we collect all mutual funds according to the following criteria: 1) The funds must be categorized by Morningstar as corporate bond general or corporate bond high quality funds. 2) All funds must have at least six years worth of return history. 3) For multiple share class funds, we collect only the largest share class. This initial search yielded 303 funds. For each fund in the sample, we then collect daily net asset values (NAVs) and distribution data from DialData. The data lists the date, the closing NAV, and the amount of the distribution, if any, on that date. The period over which daily data is collected is January 1, 1994 through September, 2001. The originating source for these data is the NASD mutual fund quote service.[19]

3.2 Daily Return Calculation and Distributions

Bond mutual funds adopt one of several different methods for reporting net asset values and distributions.[20] The most straightforward method, because it parallels the method for equity funds, entails adjusting the NAV down on the day of any distribution by the amount of the distribution. This method also intuitively matches how we expect stock prices to adjust at the ex-dividend date. However, most bond funds do not account for distributions in this manner. Most bond funds treat income and capital gains distributions differently. While capital gains distributions generally are accompanied by an equivalent reduction in NAV, income distributions are most often treated just as accrued interest is treated with bonds. The NAV of the fund is quoted without the accrued interest, but a fund redeemer is entitled to the NAV plus the accrued interest of the fund. Hence, when an income distribution is made, it has no effect on the NAV.

These different reporting conventions significantly complicate the calculation of daily fund returns on days where funds pay distributions. The correct treatment of distributions requires knowledge of a fund's accounting method and, in many cases, the percentage of the distribution that is income versus

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[19] Since our sample of funds is identified using the September 2001 disk and the daily returns are previous to this time, our sample is subject to survivorship bias. We have no reason to believe that window dressing is more or less likely for funds that survive. Additionally, DialData provides historical NAVs for surviving funds only.

[20] The details in this subsection were identified in the data and verified through independent discussions with employees of the Investment Company Institute

capital gains. We have neither in our dataset. For this reason, we eliminate all days on which a distribution is paid on the funds in our sample.

The lack of information on accrued interest means that technically we cannot calculate total daily returns. The actual total daily return would include changes in the NAV of the fund plus any interest that accrues on that day. We can, however, calculate a price return for each day. Price returns are thus calculated from this data as:

$$PRET_{i,t} = (NAV_{i,t} - NAV_{i,t-1})/ NAV_{i,t-1}, \tag{2}$$

where,

$PRET_{i,t}$ = daily price return for fund i on day t,
$NAV_{i,t}$ = net asset value of fund i at close of day t.

Daily price returns are calculated for each fund on each day over the period January 1, 1994 through September 30, 2001. A fund that exists throughout the sample period will have 83 months of return data. For eight funds we were unable to find daily return data, reducing our sample of funds to 295. Table 7 presents details of the sample with respect to the types of funds and the fiscal year-ends of the funds. We note that the most popular disclosure schedule is June and December. However, 70% of the sample reports in months other than these.[21]

A small number of missing observations are evident in the data. For a subset of these missing observations, we cross-checked these missing observations with data from "Yahoo!". In all of the cases checked, Yahoo! was also missing those same observations, suggesting it was the original source of data that was lacking these observations. For each of the missing observations, returns on that day and the day following cannot be calculated. In all, 0.33 percent of all observations of fund returns cannot be calculated because of missing data. Additionally, we drop 2.1% of all return observations due to reported distributions.

3.3. Market Model Methodology and Results

The first step in the analysis is to estimate a market model for each fund in the sample. Our intuition is that there is very little difference between the price returns we calculate and daily total returns (including accrued interest). However, to avoid an apples-to-oranges comparison, we specify a market model with indexes that proxy only for price returns. We relate the daily price returns to our sample of mutual funds

[21] Carhart, Kaniel, Musto and Reed (2001) find evidence that equity fund managers engage in trading that temporarily inflates NAVs on the last day of the year. Such behavior, if systematically employed in bond portfolios, might influence our findings. However, given that 70 percent of our sample has non-December reporting periods, we doubt that such an effect drives our subsequent results.

to yield changes on government and corporate bonds. For the government bond sector we use the yield on 10-year treasuries. For the corporate sector, we initially test whether the Moody's Aaa yield or Moody's Baa yield gives us a better fit for the funds in the sample. On this first set of regressions, we form a portfolio of all bond funds in the general category and a portfolio of all bonds in the high quality category. The returns to each of these portfolios are regressed against the bond yield indexes. The market model is thus shown in equation (3) below with three indexes:

$$Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Yaaa_t + \beta 3 * Ybaa_t + \varepsilon_{i,t} \tag{3}$$

where,

$Return_{i,t}$ = Return to the average portfolio (general or high quality) on day t,
$Yt10_t$ = percentage change in the yield on 10-year treasuries on day t,
$Yaaa_t$ = percentage change in yield on Moody's aaa corporate bond index on day t,
$Ybaa_t$ = percentage change in yield on Moody's baa corporate bond index on day t.

Table 8 shows the results from estimating four variants of equation (3) for portfolios of all general bond funds and all high quality bond funds. Obviously the coefficients on the index are negative because fund price returns are inversely correlated with bond yield changes. Including only the government index explains 90% of the variation in portfolio returns across time for both categories of funds. Adding the corporate indexes increases the R-squares to between 93 and 94%. It appears as though the fit of the market model is not materially better with one corporate index than the other. In both cases the R-square is slightly higher with the Baa index. This finding makes intuitive sense because the Baa index is further down the default risk spectrum and may do a better job of spanning the bond market in combination with the government index. A three-factor model provides little additional explanatory power.

We next run a dual index market model for each fund in the sample. We select the government yield/Baa corporate yield model for reasons stated above. The model does not appear to be well-specified for some funds in the sample, as indicated by low R-squares in several of the individual fund regressions. Out of the sample of 295 bond funds, 135 have R-squares greater than .80. An additional 65 exhibit R-squares between .70 and .80. 24 display R-squares between .60 and .70 while the remaining 71 funds have R-squares less than .60. We suspect that the low R-squares are likely the result of errors in the data. We specify several screens to attempt to filter out erroneous returns (i.e., large and opposite-signed returns on subsequent days) and deleted these observations from the sample before estimating the market models. For the next step in our analysis, we delete the 71 funds in the sample that do not exhibit an R-square of at least 60% for the market model.

With the sample limited to those funds for which our market model is well-specified, we develop an augmented market model regression to detect differences in index factor loadings for funds around disclosure periods. The augmented market model is shown below in equation 4.

$$Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Ybaa_t + \beta 3_i * DiscDum * Yt10_t + \beta 4_i * DiscDum * Ybaa_t + \varepsilon_{i,t} \quad (4)$$

where,

DiscDum = 1 if day t is within 5 days of the end of the fund's fiscal year or half-year end, 0 otherwise.

On most days of the year, *DiscDum* will be zero. DiscDum will be 1 on the last five trading days of the reporting period and the first five days of the following reporting period.[22] The interpretation of the interaction terms is that they represent the average incremental difference in loading on the indexes around disclosure periods. Since the β1 (β2) coefficient is negative, a negative and significant β3 (β4) indicates heightened sensitivity to the yield changes in the government (corporate) bond market. A positive and significant coefficient is consistent with less sensitivity to those sectors of the bond market.

Our procedure is to run the model in equation (4) for each of the 224 funds in the sample that appear well specified by our dual-index market model. We then examine the sign and significance of the interaction coefficients across the sample. We undertake this portion of the analysis separately for general and high quality funds. Tabulations of the numbers of funds with significant interaction coefficients and their signs are presented in Tables 9 (general quality funds) and 10 (high quality funds). Each table has three panels that subdivide the sample on the degree of fit of the market model.

First consider the general funds in Table 9. Of the 148 funds, 18.9 percent (28 funds) exhibit β3 coefficients that are significantly different from zero at the five percent level. Fourteen percent (21 funds) have significant β4 coefficients at the five percent level. Of course, statistically we would expect that in a sample of 148 funds, five percent (between 7 and 8 funds) would show a significant coefficient (at the five percent level) even in the absence of any true relationship between the funds' returns and the interacted variable. We measure whether the percentage observed is statistically different than the alpha-level significance threshold by specifying a binomial probability test. The test measures the probability of observing a certain percentage of significant coefficients given that we expect the alpha-level percentage of funds to display a by-chance sensitivity to the interacted variable. For example, in the case of the β3 coefficient in the first row of Panel A, the binomial test will measure the likelihood of observing a significant coefficient for 18.9% of the sample (28 funds) under the null that 5% will display a significant coefficient even in the absence of any true differential sensitivity to the government index around reporting periods. The binomial probability for observing exactly y significant coefficients is shown in equation (5):

$$p(y) \quad = \quad \binom{n}{y} p^{y} q^{n-y} \tag{5}$$

where,

p(y) = the probability of observing exactly y significant coefficients,
n = the total number of funds for which the market model is run,
p = the alpha level of significance for identifying funds that are differentially sensitive to the given index,
q = (1-p).

To generate a test statistic, we must calculate p(y) for each number of funds less than the observed number of significant coefficients and sum these probabilities. Subtracting this sum from 1 gives us the p-value on our test. For example, the probability of observing 28 or more significant β3 coefficients is {1-[p(1)+p(2) + p(3) + … + p(27)]}. In this case, the p-value is $3*10^{-10}$.

All three panels of Table 9 show that for various alpha-level thresholds for identifying significant β3 coefficients, the percentage of funds identified is highly statistically different from the alpha-level. We conclude that the significant coefficients strongly suggest that some funds have reliably different sensitivities to the government bond index around reporting periods.

The third and fourth columns of Table 9 document the percentages of coefficients that are positively and negatively significant. A positive β3 coefficient suggests a decline in the sensitivity to the government index around reporting periods and would be consistent with funds holding relatively less government debt. For the tests of significance on the signed coefficients, the threshold significance level is the alpha-level divided by two. We find that the number of positively significant β3 coefficients is statistically greater than that expected by chance. However, the statistical significance is not as uniformly strong as that for unsigned significant coefficients. The number of β3 coefficients that are negative and significant are greater than the number that are positive and the significance levels are also greater. The evidence here suggests that some funds are reducing their government exposure around reporting periods though more funds appear to be increasing their government bond exposure.

[22] In an alternative specification, we designated the six days surrounding the end of the month as the reporting period. Results were qualitatively the same as those subsequently presented.

We find corroborating results for the β4 coefficients which signal altered exposure to corporate bonds around reporting periods. The number of coefficients that are significant is far greater than we would expect by chance. Within the corporate bond sector the results seem more evenly split between funds that increase and funds that decrease exposure. Taken together, the results for the β3 and β4 coefficients are consistent with a clientele of window-dressing bond fund managers. Some of these managers appear to increase their exposure to government bonds, presumably in an effort to increase the perceived safety of their portfolio. A second group of funds increase exposure to the corporate bond market, most likely in an effort to increase the yield on the portfolio.

Perhaps a stronger test of window dressing would be to document those funds that display both β3 and β4 coefficients that are significant and of opposite signs. In every single case of a significant β3 or β4 coefficient, the other coefficient was of the opposite sign, but not necessarily significant at traditional levels. Of the 148 funds in the general bond fund sample, 16 exhibit β3 and β4 coefficients that are both significant at the 5% level or better and of the opposite sign.[23] Of these 16, eight display negative β3 coefficients and positive β4 coefficients consistent with a quality-increasing strategy. If we assume that there is no altered sensitivity to these indexes around reporting periods, we would expect by chance to find both β3 and β4 coefficients significant at the five percent level in only $(.05)^2 = .25$ percent of all funds. We find it in approximately 11 percent of funds.[24] Six of the 16 funds have reporting periods in June and December, five report in April and October, three report in March and September, and one each report in January/July and February/August. These results suggest that specific reporting months are not driving the findings.

As a robustness check, we estimated equation (4) with a modified dependent variable. Instead of estimating the model with the raw price returns for each fund as the dependent variable, we formed a long-short portfolio for each fund in the sample and used this portfolio as the dependent variable. The long short portfolio is long on the fund and short on an equally-weighted portfolio of all funds in the sample that do not have the same reporting period schedule as the fund. The idea behind this construction is to control for systematic changes in the bond market that may be affecting all funds and not just the fund in question. The results are qualitatively similar to the reported results in Table 9. For example, we find 31 of 148 long-short portfolios (20.9 percent) with β3 coefficients significant at the five percent level. 12.1 percent were negative and significant and 8.8 percent were positive and significant. A total of

[23] Seven (three) funds display coefficients that are of opposite signs and significant at the 1 percent (.1 percent) level.

[24] If we limit the sample to only those funds with market model R-squares greater than .8, we find 10 funds (11 percent) with both coefficients significant.

18 funds display β3 and β4 coefficients that are both significant at the five percent level and show the opposite sign.

Table 10 presents the results for the sample of high quality bond funds. As with the general funds, there is strong evidence that the number of significant β3 and β4 coefficients are not just statistical artifacts. The results for altered government exposure are stronger than that for altered corporate exposure, however both are significant at traditional levels. The noticeable difference between the results for high quality funds and those for general funds is that the evidence is stronger that the bulk of altered bond market exposure comes in the form of funds increasing government exposure and decreasing corporate exposure. For example, the first row of panel A shows that the percentage of funds with negative β3 coefficients significant at the five percent level is 14.5 percent. This percentage is significantly different from five percent. However, the number of funds we detect with positive β3 coefficients significant at the five percent level is not different from five percent. We find the opposite result with the β4 coefficients; there is statistical evidence of reduced corporate exposure for funds in the sample, but no significant evidence of increased corporate exposure. These results are generally consistent across all three panels of Table 10. The findings are intuitively appealing in that we would expect that high quality funds would be much more likely to attempt to increase their perceived quality around reporting periods than to reduce quality. The results also corroborate our findings in the portfolio holdings analysis. In Table 1 we saw that the changes in magnitude of government bond holdings in disclosure periods are more pronounced for high-quality funds than for general quality funds. We also could not reliably conclude that high quality funds had any statistical movement into lower quality corporate debt around disclosure periods. We further saw in Tables 3 and 4 that aggregate measures of bond quality generally increased for high quality funds around disclosure periods. This increase in quality was not evident for general bond funds, likely because some of the funds in that category increase yields by moving into lower grade corporate debt.

4. Conclusions

This paper has investigated the degree to which window dressing behavior exists in bond mutual funds. This is an important issue for several reasons. First, bond funds hold about one third of all assets invested in long-term mutual funds and thus represent a substantial, though heretofore unexplored, mutual fund asset class with respect to window dressing. Second, the use of bond funds and the data that we collect allow us to examine window dressing behavior in more detail than have previous studies of equity funds or money market funds. The finer breakdowns in asset quality for bond funds compared to money market funds gives us the ability to detect more subtle movements in portfolio credit quality. For example, we can (and do) detect two distinct types of window dressing behavior; one that increases portfolio quality and another that bolsters yields at disclosure. Third, in regards to window dressing behavior, bond funds are intuitively more appealing to study than money market funds since the longer maturities of the securities in the portfolio make any window dressing more deliberate on the manager's part and more costly to investors.

Using two different methodologies, portfolio holdings and daily returns, we find relatively strong evidence of window dressing behavior in both high quality and general bond funds. Specifically, for high quality bond funds, the portfolio composition analysis suggests that window dressing predominantly takes the form of moving into government securities and away from corporate securities for reporting purposes. Furthermore, the magnitudes of our results are not trivial. High-quality bond fund managers on average appear to allocate an additional five percent of their portfolios to government securities in official reporting periods. This reallocation causes several measures of aggregate bond fund quality to be significantly higher in disclosure periods for these funds. Our daily return analysis confirms these results. We find a significant percentage of high quality funds for which the return generating process tilts toward government securities and away from corporate securities around reporting periods.

For general quality funds we detect this same behavior in both our portfolio composition and daily return analyses. However, we also detect evidence of a different type of window dressing behavior in some funds – movement into lower quality bonds presumably to increase the yield on the portfolio. This altering of the portfolio is evidenced by greater exposures in reporting periods to non-investment grade debt in the portfolio composition analysis and by increased weightings on a lower quality corporate bond index in the daily return analysis.

Finally, our findings clearly have regulatory implications. Investors in bond funds may bear implicit and explicit costs due to window dressing. However, from an enforcement perspective there has heretofore been significant difficulty in identifying those funds that are engaging in such activities. Our daily returns methodology in section 3 suggests a mechanism for identifying funds with return patterns consistent with window dressing. Using daily returns and well-specified market models, regulators can screen the universe of funds to isolate a manageable sample of funds that appears most likely to be cosmetically managing their portfolios at fiscal reporting periods.

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Table 1: Determinants of Broad Bond Quality Portfolio Percentages.
The broad bond quality categories are government, investment grade corporate, non-investment grade corporate and non-rated. All variables are dummy variables. T-statistics are in parenthesis.

Sample:	**Full Sample**				**Corporate General Bond Data Points**				**Corporate High-Quality Bond Data Points**			
	% bonds held in the following categories				*% bonds held in the following categories*				*% bonds held in the following categories*			
	Govt	**Investment Grade Corporates (AAA-BBB)**	**Non-Investment Grade Corporates (BB-Sub B)**	**NA/NR**	**Govt**	**Investment Grade Corporates (AAA-BBB)**	**Non-Investment Grade Corporates (BB-Sub B)**	**NA/NR**	**Govt**	**Investment Grade Corporates (AAA-BBB)**	**Non-Investment Grade Corporates (BB-Sub B)**	**NA/NR**
Intercept	34.100*** (23.426)	59.973*** (42.696)	2.308*** (4.828)	3.461*** (8.154)	26.624*** (16.501)	62.715*** (40.560)	6.655*** (10.259)	3.944*** (7.701)	35.629*** (15.341)	57.617*** (25.447)	2.755*** (6.762)	3.724*** (6.429)
June	-5.061*** (3.759)	4.597*** (3.539)	-0.001 (0.003)	0.497 (1.265)	-5.684*** (3.450)	4.470*** (2.832)	0.155 (0.234)	1.082** (2.069)	-4.062* (1.753)	4.879** (2.160)	-0.270 (0.664)	-0.499 (0.864)
September	-1.781 (1.279)	2.898** (2.156)	-0.816* (1.784)	-0.326 (0.803)	-1.552 (0.909)	2.700 (1.650)	-0.998 (1.454)	-0.136 (0.251)	-2.371 (0.990)	3.466 (1.485)	-0.499 (1.189)	-0.683 (1.144)
December	-4.143*** (3.002)	5.319*** (3.995)	-0.279 (0.616)	-0.879** (2.185)	-4.077** (2.401)	5.393*** (3.314)	-0.145 (0.212)	-1.188** (2.204)	-4.333* (1.840)	5.333** (2.323)	-0.547 (1.325)	-0.371 (0.631)
Non-QuarterEnd	-7.536*** (2.916)	6.388** (2.562)	2.797*** (3.296)	-1.618** (2.147)	-10.324*** (3.422)	8.149*** (2.819)	3.437*** (2.834)	-1.233 (1.287)	-1.404 (0.287)	2.389 (0.501)	1.321 (1.539)	-2.264* (1.855)
1997	4.985*** (2.872)	-4.893*** (2.921)	-0.964* (1.692)	0.988* (1.952)	6.367*** (3.002)	-6.498*** (3.197)	-1.159 (1.359)	1.351** (2.006)	2.477 (0.826)	-2.041 (0.698)	-0.595 (1.132)	0.364 (0.486)
1998	2.272* (1.813)	-1.756 (1.452)	0.223 (0.541)	-0.620* (1.695)	3.852** (2.535)	-3.689** (2.534)	0.517 (0.847)	-0.635 (1.317)	-0.595 (0.271)	1.716 (0.802)	-0.269 (0.699)	-0.601 (1.097)
1999	-2.900** (2.227)	3.997*** (3.182)	0.258 (0.603)	-1.259*** (3.315)	-1.450 (0.912)	2.488 (1.634)	0.503 (0.787)	-1.532*** (3.036)	-5.390** (2.395)	6.640*** (3.027)	-0.181 (0.459)	-0.822 (1.464)
General Style	-6.743*** (7.086)	1.524 (1.660)	4.603*** (14.734)	0.648** (2.336)	NA	NA	NA	NA	NA	NA	NA	NA
Disclosure	3.516*** (3.299)	-4.022*** (3.911)	0.794** (2.269)	-0.243 (0.783)	2.679** (2.104)	-3.692*** (3.026)	0.933* (1.822)	0.120 (0.297)	4.996*** (2.607)	-4.505** (2.412)	0.514 (1.528)	-0.946** (1.979)
N	3170	3170	3170	3170	1987	1987	1987	1987	1183	1183	1183	1183
Adj-R-squared	0.031	0.020	0.073	0.009	0.021	0.022	0.008	0.011	0.010	0.014	0.002	0.004

*** significant at the 1 percent level;
** significant at the 5 percent level;
* significant at the 10 percent level.

Table 2: Determinants of Fine Bond Quality Portfolio Percentages and Aggregate Bond Quality for All Funds.
The fine bond quality categories are government, AAA, AA, A, BBB, BB, B, Sub B and non-rated. All variables are dummy variables. T-statistics are in parenthesis.

Sample: Full Sample

	% bonds held in the following categories									*Aggregate Bond Quality Measures*				
	Govt.	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**SubB**	**Not Rated**	**Morning-star**	**Method 1**	**Method 2**	**Method 3**	**Method 4**
Intercept	34.100*** (23.426)	23.859*** (18.661)	7.139*** (19.395)	19.269*** (28.226)	9.706*** (13.946)	1.506*** (4.879)	0.731*** (3.049)	0.071 (1.193)	3.461*** (8.154)	3.941*** (92.808)	6.394*** (138.459)	6.239*** (116.637)	6.036*** (161.018)	5.898*** (132.224)
June	-5.061*** (3.759)	3.182*** (2.691)	-0.022 (0.065)	0.780 (1.236)	0.657 (1.020)	-0.082 (0.287)	-0.022 (0.100)	0.103* (1.872)	0.497 (1.265)	-0.029 (0.752)	-0.098** (2.287)	-0.120** (2.426)	-0.050 (1.429)	-0.069* (1.683)
September	-1.781 (1.279)	2.314* (1.892)	-0.139 (0.395)	0.480 (0.735)	0.243 (0.365)	-0.485 (1.641)	-0.341 (1.484)	0.009 (0.164)	-0.326 (0.803)	0.091** (2.241)	0.009 (0.203)	0.024 (0.462)	0.028 (0.792)	0.041 (0.971)
December	-4.143*** (3.002)	2.454** (2.025)	0.268 (0.769)	1.340** (2.071)	1.257* (1.904)	-0.109 (0.371)	-0.171 (0.754)	0.001 (0.017)	-0.879** (2.185)	-0.024 (0.602)	-0.073 (1.656)	-0.033 (0.649)	-0.027 (0.751)	0.008 (0.201)
Non-QuarterEnd	-7.536*** (2.916)	-0.858 (0.378)	2.138*** (3.272)	2.059* (1.698)	3.050** (2.468)	1.430*** (2.611)	1.239*** (2.912)	0.127 (1.206)	-1.618** (2.147)	-0.128* (1.682)	-0.314*** (3.824)	-0.241** (2.535)	-0.230*** (3.458)	-0.165** (2.089)
1997	4.985*** (2.872)	-1.260 (0.827)	0.134 (0.306)	-1.309 (1.608)	-2.458*** (2.961)	-0.726** (1.974)	-0.205 (0.715)	-0.033 (0.468)	0.988* (1.952)	-0.061 (1.205)	0.173*** (3.143)	0.129** (2.017)	0.118*** (2.647)	0.079 (1.481)
1998	2.272* (1.813)	-1.029 (0.935)	0.261 (0.822)	-0.514 (0.875)	-0.473 (0.789)	0.281 (1.059)	-0.029 (0.140)	-0.030 (0.584)	-0.620* (1.695)	0.054 (1.470)	0.060 (1.520)	0.088* (1.918)	0.041 (1.264)	0.066* (1.708)
1999	-2.900** (2.227)	2.496** (2.183)	1.001*** (3.040)	0.240 (0.393)	0.260 (0.418)	0.317 (1.148)	0.020 (0.092)	-0.079 (1.485)	-1.259*** (3.315)	0.019 (0.506)	-0.022 (0.541)	0.034 (0.717)	0.013 (0.386)	0.063 (1.587)
General Style	-6.743*** (7.086)	-2.635*** (3.153)	-0.750*** (3.119)	-2.099*** (4.704)	7.008*** (15.406)	3.000*** (14.874)	1.411*** (9.004)	0.192*** (4.937)	0.648** (2.336)	-0.326*** (11.744)	-0.444*** (14.715)	-0.473*** (13.539)	-0.380*** (15.508)	-0.406*** (13.923)
Disclosure	3.516*** (3.299)	-3.331*** (3.558)	-0.104 (0.387)	-0.176 (0.351)	-0.411 (0.807)	0.453** (2.003)	0.336* (1.912)	0.006 (0.134)	-0.243 (0.783)	-0.008 (0.243)	0.026 (0.770)	0.037 (0.945)	-0.008 (0.288)	0.002 (0.056)
N	3170	3170	3170	3170	3170	3170	3170	3170	3170	3127	3170	3170	3170	3170
Adj-R-squared	0.031	0.012	0.008	0.007	0.073	0.073	0.029	0.007	0.009	0.047	0.073	0.059	0.077	0.061

*** significant at the 1 percent level;
** significant at the 5 percent level;
* significant at the 10 percent level.

Table 3: Determinants of Fine Bond Quality Portfolio Percentages and Aggregate Bond Quality for Corporate General Bond Funds.
The fine bond quality categories are government, AAA, AA, A, BBB, BB, B, Sub B and non-rated. All variables are dummy variables. T-statistics are in parenthesis.

Sample: *Corporate Bond General*

	% bonds held in the following categories									*Aggregate Bond Quality Measures*				
	Govt.	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**SubB**	**Not Rated**	**Morning-star**	**Method 1**	**Method 2**	**Method 3**	**Method 4**
Intercept	26.624*** (16.501)	22.576*** (15.742)	6.385*** (14.877)	17.604*** (23.606)	16.150*** (18.330)	4.300*** (10.390)	2.093*** (6.390)	0.262*** (3.191)	3.944*** (7.701)	3.640*** (70.957)	5.970*** (104.150)	5.793*** (88.279)	5.685*** (119.485)	5.527*** (99.314)
June	-5.684*** (3.450)	3.145** (2.148)	-0.085 (0.193)	0.778 (1.022)	0.632 (0.703)	-0.029 (0.068)	0.022 (0.065)	0.162* (1.931)	1.082** (2.069)	-0.062 (1.180)	-0.126** (2.146)	-0.174*** (2.601)	-0.074 (1.527)	-0.117** (2.067)
September	-1.552 (0.909)	2.846* (1.875)	-0.165 (0.362)	0.417 (0.528)	-0.398 (0.427)	-0.650 (1.484)	-0.360 (1.040)	0.012 (0.137)	-0.136 (0.251)	0.062 (1.136)	0.037 (0.617)	0.044 (0.627)	0.054 (1.065)	0.059 (1.003)
December	-4.077** (2.401)	1.488 (0.986)	0.221 (0.489)	1.730** (2.205)	1.954** (2.108)	0.023 (0.052)	-0.178 (0.516)	0.011 (0.125)	-1.188** (2.204)	-0.051 (0.945)	-0.100 (1.663)	-0.047 (0.679)	-0.054 (1.071)	-0.006 (0.104)
NonQuart End	-10.324*** (3.422)	-2.554 (0.952)	2.497*** (3.111)	4.788*** (3.433)	3.418** (2.075)	1.507* (1.948)	1.738*** (2.837)	0.192 (1.249)	-1.233 (1.287)	-0.181* (1.876)	-0.452*** (4.219)	-0.397*** (3.234)	-0.343*** (3.854)	-0.294*** (2.821)
1997	6.367*** (3.002)	-1.987 (1.054)	-0.094 (0.167)	-2.232** (2.277)	-2.185* (1.886)	-0.765 (1.406)	-0.328 (0.762)	-0.066 (0.614)	1.351** (2.006)	-0.021 (0.317)	0.196*** (2.604)	0.135 (1.570)	0.126** (2.012)	0.072 (0.981)
1998	3.852** (2.535)	-2.643** (1.957)	0.305 (0.755)	-1.644** (2.341)	0.293 (0.353)	0.620 (1.590)	-0.047 (0.152)	-0.056 (0.720)	-0.635 (1.317)	0.039 (0.809)	0.059 (1.101)	0.088 (1.425)	0.024 (0.538)	0.050 (0.945)
1999	-1.450 (0.912)	1.199 (0.849)	1.039** (2.458)	-0.324 (0.441)	0.574 (0.662)	0.556 (1.363)	0.048 (0.149)	-0.101 (1.251)	-1.532*** (3.036)	0.025 (0.496)	-0.015 (0.270)	0.054 (0.830)	0.007 (0.147)	0.068 (1.244)
Disclosure	2.679** (2.104)	-3.585*** (3.168)	-0.022 (0.066)	-0.036 (0.061)	-0.049 (0.070)	0.459 (1.405)	0.468* (1.810)	0.006 (0.094)	0.120 (0.297)	-0.016 (0.400)	-0.013 (0.291)	-0.019 (0.358)	-0.041 (1.080)	-0.045 (1.033)
N	1987	1987	1987	1987	1987	1987	1987	1987	1987	1963	1987	1987	1987	1987
Adj-R-squared	0.021	0.010	0.006	0.007	0.003	0.007	0.004	0.001	0.011	0.002	0.015	0.009	0.011	0.006

*** significant at the 1 percent level
** significant at the 5 percent level
* significant at the 10 percent level

Table 4: Determinants of Fine Bond Quality Portfolio Percentages and Aggregate Bond Quality for Corporate High-Quality Bond Funds.
The fine bond quality categories are government, AAA, AA, A, BBB, BB, B, Sub B and non-rated. All variables are dummy variables. T-statistics are in parenthesis.

Sample: *Corporate Bond High-Quality*

	% bonds held in the following categories									*Aggregate Bond Quality Measures*				
	Govt.	**AAA**	**AA**	**A**	**BBB**	**BB**	**B**	**SubB**	**Not Rated**	**Morning-star**	**Method 1**	**Method 2**	**Method 3**	**Method 4**
Intercept	35.629***	21.399***	7.142***	18.338***	10.738***	1.890***	0.799***	0.066	3.724***	3.898***	6.364***	6.197***	5.989***	5.840***
	(15.341)	(10.679)	(13.181)	(16.573)	(12.922)	(6.622)	(4.123)	(1.531)	(6.429)	(67.383)	(108.716)	(88.538)	(135.220)	(104.920)
June	-4.062*	3.260	0.084	0.840	0.696	-0.180	-0.094	0.004	-0.499	0.025	-0.052	-0.029	-0.009	0.011
	(1.753)	(1.631)	(0.155)	(0.761)	(0.839)	(0.632)	(0.484)	(0.082)	(0.864)	(0.428)	(0.885)	(0.418)	(0.193)	(0.206)
September	-2.371	1.527	-0.083	0.759	1.263	-0.219	-0.290	0.010	-0.683	0.139**	-0.042	-0.012	-0.015	0.012
	(0.990)	(0.740)	(0.148)	(0.666)	(1.474)	(0.745)	(1.453)	(0.232)	(1.144)	(2.328)	(0.700)	(0.160)	(0.331)	(0.212)
December	-4.333*	4.199**	0.331	0.783	0.020	-0.367	-0.166	-0.015	-0.371	0.023	-0.024	-0.007	0.021	0.036
	(1.840)	(2.066)	(0.602)	(0.698)	(0.024)	(1.268)	(0.843)	(0.338)	(0.631)	(0.386)	(0.406)	(0.105)	(0.469)	(0.636)
NonQuart End	-1.404	2.995	1.276	-4.228*	2.346	1.234**	0.098	-0.011	-2.264*	-0.020	-0.007	0.095	0.019	0.109
	(0.287)	(0.710)	(1.118)	(1.814)	(1.340)	(2.052)	(0.240)	(0.1180	(1.855)	(0.160)	(0.054)	(0.646)	(0.200)	(0.931)
1997	2.477	-0.160	0.520	0.351	-2.752***	-0.635*	0.013	0.026	0.364	-0.125*	0.123	0.107	0.097*	0.082
	(0.826)	(0.062)	(0.743)	(0.246)	(2.565)	(1.722)	(0.053)	(0.472)	(0.486)	(1.675)	(1.634)	(1.186)	(1.695)	(1.146)
1998	-0.595	1.789	0.195	1.564	-1.832**	-0.303	0.014	0.019	-0.601	0.080	0.059	0.086	0.068	0.092
	(0.271)	(0.944)	(0.380)	(1.495)	(2.332)	(1.122)	(0.078)	(0.475)	(1.097)	(1.472)	(1.059)	(1.295)	(1.614)	(1.741)
1999	-5.390**	4.832**	0.930*	1.218	-0.340	-0.106	-0.035	-0.040	-0.822	0.011	-0.031	0.006	0.027	0.060
	(2.395)	(2.489)	(1.770)	(1.136)	(0.422)	(0.382)	(0.188)	(0.968)	(1.464)	(0.193)	(0.548)	(0.086)	(0.627)	(1.108)
Disclosure	4.996***	-2.787*	-0.260	-0.295	-1.163*	0.414*	0.093	0.007	-0.946**	0.012	0.100**	0.142**	0.054	0.092**
	(2.607)	(1.686)	(0.582)	(0.324)	(1.696)	(1.757)	(0.582)	(0.190)	(1.979)	(0.244)	(2.060)	(2.461)	(1.485)	(2.006)
N	1183	1183	1183	1183	1183	1183	1183	1183	1183	1164	1183	1183	1183	1183
Adj-R-squared	0.010	0.005	0.001	0.001	0.011	0.007	0.004	0.004	0.004	0.008	0.003	0.002	0.001	0.001

*** significant at the 1 percent level;
** significant at the 5 percent level;
* significant at the 10 percent level.

Table 5: Credit Analysis Pairs Analysis.
In the Government, Investment Grade Corporate, Non-Investment Grade Corporate and NA/NR columns a positive (negative) indicates the percentage of bond holdings in question was higher (lower) in the disclosure period than it was in the non-disclosure period.

				Average (Disclosure % Holdings – Non-Disclosure % Holdings) in the following:			
Non-Disclosure Credit Analysis Date	**Disclosure Credit Analysis Date**	**Group #**	**Number of Credit Analysis Pairs**	**Government**	**Investment Grade Corporate (AAA-BBB)**	**Non-Investment Grade Corporate (BB-Sub B)**	**NA/NR**
Observations where Disclosure Follows Non-Disclosure							
December 31, 1997	March 31, 1998	1	42	1.270	-2.027	0.440	0.318
March 31, 1998	June 30, 1998	2	62	-4.758**	4.645**	0.943	-0.830
June 30, 1998	September 30, 1998	3	41	2.128	-1.241	-0.425	-0.462
September 30, 1998	December 31, 1998	4	39	-0.089	0.577	0.623	-1.110
December 31, 1998	March 31, 1999	5	45	1.217	-2.899	0.101	1.581
March 31, 1999	June 30, 1999	6	69	-7.182**	6.488**	0.512	0.182
June 30, 1999	September 30, 1999	7	30	1.267	-2.363	-0.260	1.356
September 30, 1999	December 31, 1999	8	19	2.051	-1.968	-0.116	0.033
December 31, 1999	March 31, 2000	9	11	-0.048	1.978	0.251	-2.181
March 31, 2000	June 30, 2000	10	16	-1.825	0.271	-0.779	2.344
June 30, 2000	September 30, 2000	11	10	8.435	-3.085	0.222	-5.552***
September 30, 2000	December 31, 2000	12	27	0.127	0.398	-0.728	0.204
Observations where Non-Disclosure Follows Disclosure							
March 31, 1998	December 31, 1997	13	65	-0.755	0.872	-0.127	0.010
June 30, 1998	March 31, 1998	14	34	5.800*	-7.696**	0.475	1.421
September 30, 1998	June 30, 1998	15	54	-1.361	0.955	0.555	-0.149
December 31, 1998	September 30, 1998	16	36	3.949	-3.694	0.122	-0.377
March 31, 1999	December 31, 1998	17	41	1.923	-2.783	-0.074	0.934
June 30, 1999	March 31, 1999	18	50	3.871*	-5.158**	0.213	1.073
September 30, 1999	June 30, 1999	19	39	-1.664	1.192	0.306	0.166
December 31, 1999	September 30, 1999	20	10	-3.127	4.993*	2.517	-4.383
March 31, 2000	December 31, 1999	21	21	1.660	-0.991	-0.477**	-0.196
June 30, 2000	March 31, 2000	22	6	2.093	-1.847	0.087	-0.333
September 30, 2000	June 30, 2000	23	21	2.541	-4.346	0.233	1.590
December 31, 2000	September 30, 2000	24	31	6.010**	-11.150***	3.012	2.115
			# Positive Cases:	**15**	**10**	**16**	**14**
			# Negative Cases:	**9**	**14**	**8**	**10**

*** significant from zero at the 1 percent level;
** significant from zero at the 5 percent level;
* significant from zero at the 10 percent level.

Table 6: **Test of Differences of Pairs to More Deeply Control for Calendar Effects.** ***Average (% Holding at Ending Date –% Holding at Beginning Date) in the following:***

Corres-ponds to Group # in Table 5	Disclosure Date	Beginning Analysis Date	Ending Credit Analysis Date	Number of Credit Analysis Pairs	Government	Investment Grade Corporate (AAA-BBB)	Non-Investment Grade Corporate (BB-Sub B)	NA/NR
Group 1	March 31, 1998	December 31, 1997	March 31, 1998	42	1.270	-2.027	0.440	0.318
Group 13	December 31, 1997	December 31, 1997	March 31, 1998	65	0.755	-0.872	0.127	-0.010
			Difference of the two groups		**0.515**	**-1.155**	**0.313**	**0.328**
Group 2	June 30, 1998	March 31, 1998	June 30, 1998	62	-4.758	4.645	0.943	-0.830
Group 14	March 31, 1997	March 31, 1998	June 30, 1998	34	-5.800	7.696	-0.475	-1.421
			Difference of the two groups		**1.042**	**-3.051**	**1.418**	**0.591**
Group 3	September 30, 1998	June 30, 1998	September 30, 1998	41	2.128	-1.241	-0.425	-0.462
Group 15	June 30, 1998	June 30, 1998	September 30, 1998	54	1.361	-0.955	-0.555	0.149
			Difference of the two groups		**0.767**	**-0.286**	**0.130**	**-0.611**
Group 4	December 31, 1998	September 30, 1998	December 31, 1998	39	-0.089	0.577	0.623	-1.110
Group 16	September 30, 1998	September 30, 1998	December 31, 1998	36	-3.949	3.694	-0.122	0.377
			Difference of the two groups		**3.860**	**-3.117**	**0.745**	**-1.487**
Group 5	March 31, 1999	December 31, 1998	March 31, 1999	45	1.217	-2.899	0.101	1.581
Group 17	December 31, 1998	December 31, 1998	March 31, 1999	41	-1.923	2.783	0.074	-0.934
			Difference of the two groups		**3.140**	**-5.682**	**0.027**	**2.515**
Group 6	June 30, 1999	March 31, 1999	June 30, 1999	69	-7.182	6.488	0.512	0.182
Group 18	March 31, 1999	March 31, 1999	June 30, 1999	50	-3.871	5.158	-0.213	-1.073
			Difference of the two groups		**-3.311**	**1.33**	**0.725**	**1.255**
Group 7	September 30, 1999	June 30, 1999	September 30, 1999	30	1.267	-2.363	-0.260	1.356
Group 19	June 30, 1999	June 30, 1999	September 30, 1999	39	1.664	-1.192	-0.306	-0.166
			Difference of the two groups		**-0.397**	**-1.171**	**0.046**	**1.522**
Group 8	December 31, 1999	September 30, 1999	December 31, 1999	19	2.051	-1.968	-0.116	0.033
Group 20	September 30, 1999	September 30, 1999	December 31, 1999	10	3.127	-4.993	-2.517	4.383
			Difference of the two groups		**-1.076**	**3.025**	**2.401**	**-4.35**
Group 9	March 31, 2000	December 31, 1999	March 31, 2000	11	-0.048	1.978	0.251	-2.181
Group 21	December 31, 1999	December 31, 1999	March 31, 2000	21	-1.660	0.991	0.477	0.196
			Difference of the two groups		**1.612**	**0.987**	**-0.226**	**-2.377**
Group 10	June 30, 2000	March 31, 2000	June 30, 2000	16	-1.825	0.271	-0.779	2.344
Group 22	March 31, 2000	March 31, 2000	June 30, 2000	6	-2.093	1.847	-0.087	0.333
			Difference of the two groups		**0.268**	**-1.576**	**-0.692**	**2.011**
Group 11	September 30, 2000	June 30, 2000	September 30, 2000	10	8.435	-3.085	0.222	-5.552
Group 23	June 30, 2000	June 30, 2000	September 30, 2000	21	-2.541	4.346	-0.233	-1.590
			Difference of the two groups		**10.976**	**-7.431**	**0.455**	**-3.962**
Group 12	December 31, 2000	September 30, 2000	December 31, 2000	27	0.127	0.398	-0.728	0.204
Group 24	September 30, 2000	September 30, 2000	December 31, 2000	31	-6.010	11.150	-3.012	-2.115
			Difference of the two groups		**6.137**	**-10.752**	**2.284**	**2.319**
NUMBER OF POSITIVE CASES FOR THE DIFFERENCES					9	3	10	7
NUMBER OF NEGATIVE CASES FOR THE DIFFERENCES					3	9	2	5
AVERAGE OF THE DIFFERENCES					**1.961**	**-2.407***	**0.635****	**-0.187**
SIGNIFICANCE TEST OF THE AVERAGE OF THE DIFFERENCES (using t-distribution)					1.740	2.031	2.202	-0.260

** significant at the 5 percent level; *significant at the 10 percent level.

Table 7: Summary Statistics of the Funds used in the Daily Return Analysis

Information on the Funds in the Sample	Number of Funds
Total Number of Funds	295
Number of Corporate Bond-General Funds	179
Number of Corporate Bond-High-quality Funds	116
Funds with Disclosure Dates in:	
January and July	18
February and August	20
March and September	71
April and October	65
May and November	31
June and December	90

Table 8: Market model specifications

The table shows the result of 4 market model specifications each for General quality bond funds and High Quality bond funds. The dependent variable is the daily returns on a portfolio of 179 General bond funds or 116 High Quality bond funds. The time period is January, 1993 through August, 2001. The independent variables are the yields on up to three bond series: 10-year treasury notes, Moody's Aaa corporate bonds and Moody's Baa corporate bonds. There are 1834 daily observations. T-statistics are shown in parentheses. All coefficients are significant beyond the .1% level.

$$Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Yaaa_t + \beta 3_i * Ybaa_t + \varepsilon_{i,t} \qquad (3)$$

	Model	R-square	α_i	$\beta 1_i$	$\beta 2_i$	$B3_i$
General Bond Funds						
	I	.904	.000084	-.206		
			(5.47)	(-131.7)		
	II	.934	.000089	-.138	-.121	
			(6.99)	(-51.3)	(-29.3)	
	III	.936	.000088	-.141		-.133
			(6.99)	(-55.6)		(-30.3)
	IV	.938	.000088	-.134	-.0562	-.0815
			(7.14)	(-50.7)	(-7.26)	(-9.78)
High Quality Bond Funds						
	I	.902	.000076	-.171		
			(5.90)	(-129.8)		
	II	.926	.000079	-.120	-.0888	
			(7.09)	(-50.7)	(-24.4)	
	III	.928	.000079	-.121		-.100
			(7.14)	(-54.5)		(-25.9)
	IV	.929	.000079	-.117	-.0352	-.0676
			(7.24)	(-50.0)	(-5.13)	(-9.17)

Table 9: Significance of reporting-period interaction coefficients for General quality bond funds

Table reports the percentage of reporting-period interaction coefficients that are significant at various levels for a sample of General bond funds. Initially, the return series for each fund is employed in the two factor market model in equation (3') below. For all funds that exhibit an R-square in the regression greater than, successively, .60, .70, and .80, the model in equation (4) is estimated. The coefficients on the bond market interactive variables are collected and the percentage that are significant at three traditional levels are tabulated. These percentages are shown in the second and fifth columns in the table. The percentage of coefficients that are positive and significant and that are negative and significant are also tabulated. Asterisks and pound signs denote those percentages that are statistically significantly greater than the alpha-level in column one.

Market model: $Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Ybaa_t + \varepsilon_{i,t}$ (3')

Extended market model: $Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Ybaa_t + \beta 3_i * DiscDum* Yt10_t + \beta 4_i * DiscDum*Ybaa_t + \varepsilon_{i,t}$ (4)

Panel A: 148 General quality funds with R-square on market model > .60

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	18.9***	6.8##	12.2###	14.2***	6.8##	7.4###
1%	11.5***	4.1###	7.4###	7.4***	4.1###	3.4###
.1%	4.7***	0.7##	4.1###	4.7***	3.4###	1.4###

Panel B: 133 General quality funds with R-square on market model > .70

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	18.8***	6.0#	12.8###	12.0***	5.3	6.8##
1%	11.3***	3.8###	7.5###	6.0***	3.0###	3.0###
.1%	5.3***	0.8##	4.5###	3.0***	2.3###	0.8##

Panel C: 88 General quality funds with R-square on market model > .80

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	21.6***	6.8#	14.8###	13.6***	6.8#	6.8#
1%	12.5***	3.4###	9.1###	5.7***	3.4###	2.3#
.1%	6.8***	1.1###	5.7###	2.3***	2.3###	0.0

*** - p-value on test of difference between percentage significant and alpha-level < .001
** - p-value on test of difference between percentage significant and alpha-level < .005
* - p-value on test of difference between percentage significant and alpha-level < .01

- p-value on test of difference between percentage significant and (alpha-level/2) < .001
- p-value on test of difference between percentage significant and (alpha-level/2) < .005
- p-value on test of difference between percentage significant and (alpha-level/2) < .01

Table 10: Significance of reporting-period interaction coefficients for High quality bond funds

Table reports the percentage of reporting-period interaction coefficients that are significant at various levels for a sample of High quality bond funds. Initially, the return series for each fund is employed in the two factor market model in equation (3') below. For all funds that exhibit an R-square in the regression greater than, successively, .60, .70, and .80, the model in equation (4) is estimated. The coefficients on the bond market interactive variables are collected and the percentage that are significant at three traditional levels are tabulated. These percentages are shown in the second and fifth columns in the table. The percentage of coefficients that are positive and significant and that are negative and significant are also tabulated. Asterisks and pound signs denote those percentages that are statistically significantly greater than the alpha-level in column one.

Market model: $Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Ybaa_t + \varepsilon_{i,t}$ (3')

Extended market model: $Return_{i,t} = \alpha_i + \beta 1_i * Yt10_t + \beta 2_i * Ybaa_t + \beta 3_i * DiscDum * Yt10_t + \beta 4_i * DiscDum * Ybaa_t + \varepsilon_{i,t}$ (4)

Panel A: 76 High quality funds with R-square on market model > .60

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	19.7***	5.3	$14.5^{###}$	11.8**	$7.9^{##}$	3.9
1%	10.5***	$2.6^{#}$	$7.9^{###}$	3.9*	$2.6^{#}$	1.3
.1%	6.6***	$1.3^{###}$	$5.3^{###}$	1.3**	0.0	$1.3^{###}$

Panel B: 67 High quality funds with R-square on market model > .70

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	20.9***	6.0	$14.9^{###}$	11.9*	$9.0^{##}$	3.0
1%	11.9***	$3.0^{##}$	$9.0^{###}$	11.3**	$3.0^{##}$	1.5
.1%	7.5**	$1.5^{###}$	$6.0^{###}$	5.3**	0.0	$1.5^{###}$

Panel C: 47 High quality funds with R-square on market model > .80

	β3			β 4		
Alpha Level:	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant	Percentage coefficients significant	Percentage Positive and significant	Percentage Negative and significant
5%	21.3***	6.4	$14.9^{###}$	14.9**	$10.6^{###}$	4.3
1%	12.8***	2.1	$10.6^{###}$	6.4**	$4.3^{##}$	2.1
.1%	4.3***	$2.1^{###}$	$8.5^{###}$	2.1***	0.0	$2.1^{###}$

*** - p-value on test of difference between percentage significant and alpha-level < .001
** - p-value on test of difference between percentage significant and alpha-level < .005
* - p-value on test of difference between percentage significant and alpha-level < .01

- p-value on test of difference between percentage significant and (alpha-level/2) < .001
- p-value on test of difference between percentage significant and (alpha-level/2) < .005
- p-value on test of difference between percentage significant and (alpha-level/2) < .01