The Use of Credit Default Swaps

in Fund Tournaments

Abstract

We examine whether mutual funds use derivatives to increase fund risk due to tournament behavior, and focus in particular on the largest U.S. corporate bond funds and their use of credit default swaps (CDS). We find that by 2008, about 60% of these funds were using CDS. On average funds are net sellers of CDS and thus use CDS to increase their credit exposures rather than to hedge credit risk. Funds that underperform during the first half of a calendar year sell more multi-name CDS during the second half of the year. Since funds do not systematically change their asset allocations or trading behaviors we conclude that the increase in funds' short, multi-name CDS positions has lead to an increase in fund risk consistent with fund tournament behavior.

JEL-Classification: G11, G15, G23

Keywords: Corporate bond funds, credit default swaps, fund tournaments, derivatives, risk-shifting

An important part of the mutual fund literature, pioneered by Brown, Harlow, and Starks (1996) and Chevalier and Ellison (1997) has examined the risk-shifting incentives of mutual fund managers. One reason for a fund manager's incentive to change the risk allocation of his fund arises from a convex fund flow–performance relationship,[1] i.e., the best performing funds receive the highest inflows of new money, and the fact that the compensation of most fund managers is linked to the size of their fund and hence new fund inflows.[2] This tournament argument gives fund managers an incentive to compete for new fund inflows by simply increasing the riskiness of their funds.

While the tournament hypothesis has received a lot of attention in the literature, a largely unsettled issue is how fund managers implement risk-shifting strategies. In principle, fund managers could increase risk by shifting their funds' asset allocation towards riskier securities, increase their trading activities, or use derivatives. Schwartz (2011) shows that underperforming managers of equity funds shift their funds' asset allocations towards riskier stocks. Derivatives, however, may be a more efficient tool to increase a fund's risk because of transaction costs, especially if a fund's assets are illiquid, and because changes in a fund's asset allocation could affect the fund's tracking error.

In this paper we examine whether fund managers use derivatives to implement risk-shifting strategies and whether such risk-shifting is due to tournament behavior. In particular, we focus on fixed-income funds and their use of credit default swaps (CDS) because the relatively low liquidity of many corporate bonds should increase the attractiveness of risk-shifting strategies using derivatives relative to other strategies such as changing a fund's bond holdings.

[1] Sirri and Tufano (1998) can be considered the seminal paper in this area. Clifford, Fulkerson, Jordan, and Waldman (2010) provide an excellent summary of the fund flow–performance literature.

Furthermore, the use of CDS is common among corporate bond funds. Our data show that by 2008, 60% of the largest 100 U.S. corporate bond funds were holding CDS positions.[3] While the size of the average CDS position, measured by the notional value relative to a fund's total net assets (TNA), increased to almost 14% in 2008, some funds even hold CDS positions in excess of the fund's TNA. Furthermore, we find that on average, corporate bond funds are net sellers of CDS. Thus, funds appear to use CDS to increase their credit exposures rather than to hedge credit risk.

A significant advantage of our data is that we are able to distinguish between long and short CDS positions, and between CDS written on a particular bond (single-name CDS), or on a portfolio of bonds (multi-name CDS).[4] This information allows us to infer possible motives for entering into a particular CDS position. For example, while long CDS positions should tend to reduce a fund's credit risk, short positions increase a fund's credit risk exposure ceteris paribus. Single-name and multi-name CDS also differ in the liquidity and the level of idiosyncratic risk. Selling multi-name CDS to increase a fund's credit exposure should be especially attractive given the high liquidity of many multi-name CDS.

Our central result is that mangers who underperform during the first half of a calendar year increase their short, multi-name CDS positions during the second half of the same calendar year. This effect is especially pronounced among funds with higher asset turnovers, as well as younger funds, which still need to build their reputations, and thus have a higher incentive to engage in fund tournaments. At the same time we find no evidence that underperforming funds

---

[2] Another potential explanation are career concerns of the fund managers (see Hu, Kale, Pagani, and Subramanian, 2011 and Kempf, Ruenzi, and Thiele, 2009).
[3] This is in contrast to Almazan, Brown, Carlson, and Chapman (2004), who find that between 1994 and 2000 only a small number of equity funds, who are permitted to do so, use derivatives.
[4] Multi-name CDS are sometimes referred to as portfolio credit default swaps.

systematically change their asset compositions, either by decreasing their cash holdings or by shifting towards riskier bonds. Nor do we observe systematic increases in a fund's trading activities as measured by the fund's asset turnover. We therefore conclude that U.S. corporate bond funds use multi-name CDS to increase fund risk in response to underperformance. This result is robust to using different performance benchmarks, different measures of the extent of CDS strategies, different estimation techniques, and also excluding the whole of 2008, which was marked by unprecedented market disruptions. Since we find no evidence of risk-shifting if we compare fund performance during the second half of a calendar year with changes in CDS strategies during the first half of the following calendar year, we conclude that the use of multi-name CDS is consistent with risk-shifting due to fund tournaments.

We add to the literature on fund tournaments by analyzing how managers implement a risk-shifting strategy. Most of the existing literature focuses on measuring the relationship between past performance and the change in future return volatilities or tracking errors, e.g. Brown, Harlow, and Starks (1996), Elton, Gruber, and Blake (2003), and Chen and Pennacchi (2009).[5] In contrast, we measure fund managers' strategies directly, since our data allows us to differentiate between risk-increasing and risk-decreasing strategies. Thus, we directly observe fund managers' actions, rather than inferring strategy changes from changes in a fund's risk characteristics, and thus offer a direct test of the tournament hypothesis.

We also add to the literature on the use of derivatives by mutual funds, which has received relatively little attention so far, despite the recent investigation by the SEC into this topic.[6] Koski and Pontiff (1999) survey equity mutual funds and find that the use of derivatives is positively

---

[5] Kempf and Ruenzi (2008) find evidence of fund tournaments within fund families, while Aragon and Nanda (2010) find evidence of tournament behavior among hedge funds.

correlated with asset turnover and membership in a fund family. We corroborate these findings for corporate bond funds using reported derivatives holdings data. Johnson and Yu (2004) find that the use of derivatives among Canadian funds is negatively correlated with fund age, and positively correlated with fund size. Marin and Rangel (2006) confirm these findings for a sample of Spanish mutual funds. In addition, they find that funds that are part of a fund family, no load funds, and funds with higher management fees are ceteris paribus more likely to use derivatives. We add to this literature by focusing on a particular type of derivative, which allows us to differentiate between risk-increasing and risk-decreasing strategies, and show that the use of multi-name CDS is related to prior underperformance. In addition, we find that funds that are managed by a single manager rather than a team are more likely to use CDS. This may be because investment companies impose more constraints on derivatives usage if a fund is managed by a team rather than an individual, as shown by Almazan, Brown, Carlson, and Chapman (2004).[7]

Finally, our results contribute to the literature on the use of CDS. While the market for credit derivatives is large by any measure, we have relatively little knowledge of how and why the major participants in this market, i.e., banks, hedge funds, insurance companies and other asset managers, are using CDS (as end-users). A few authors have examined the use of CDS by banks. Mahieu and Xu (2007) and Minton, Stulz, and Williamson (2009) both analyze data from the Federal Reserve Bank of Chicago Bank Holding Company Database (BHC) about the CDS positions held by U.S. banks. They find that the use of CDS is concentrated among the larger banks, that the derivatives positions are small relative to a bank's loan portfolio, and that CDS

---

[6] See the SEC concept paper titled "Use of Derivatives by Investment Companies under the Investment Company Act of 1940" (Release No. IC-29776).
[7] See Table 5 in their more comprehensive working paper version dated December 18, 2002.

were used mostly for trading rather than for hedging purposes. In contrast, Hirtle (2009) shows that U.S. commercial banks are net buyers of credit protection, suggesting that banks may in fact be hedging. However, she too finds that the CDS positions are small relative to banks' total loan portfolios. Van Ofwegen, Verschoor, and Zwinkels (2010) analyze the relation between credit derivatives and the probability of default of the 20 largest European financial institutions. They find that the use of credit derivatives tends to increase default risk, and is thus unlikely to be motivated by hedging considerations. To the best of our knowledge, there is no study yet on the use of CDS by hedge funds, insurance companies, or other asset managers. We add to this literature by examining the use of CDS by mutual funds.

The rest of the article is structured as follows. Section I describes the data and the data sources. Section II contains our econometric analysis, and Section III concludes.

I Data

Since 2004, U.S. mutual funds are required to disclose their derivatives holdings semi-annually on Form N-Q. Searching these forms of all mutual funds contained in the CRSP survivorship-free mutual fund data base as of the end of 2008, for key words such as *credit default*, *default swap*, *CDS*, *default contract*, and *default protection* yielded hits predominantly among corporate bond funds.[8] We therefore focus our analysis on U.S. corporate bond funds, which we identify by membership in one of seven Lipper fund classes: Corporate debt funds A-rated, corporate debt funds BBB-rated, short investment grade, short-intermediate investment grade, intermediate investment grade, multi-sector income, and high current yield funds.

[8] For instance, equity mutual funds are not allowed to hold CDS positions. Indeed, we found that only one fund out of the largest 30 U.S. equity funds held a small CDS position.

To keep the data collection of CDS positions, which have to be collected by hand, manageable, we focus on the largest 100 U.S. corporate bond funds by TNA, which are included in the CRSP survivorship-free mutual fund data base as of the end of the second quarter of 2004. This is the most relevant set of corporate bond funds for investors and regulators, and makes up 80.3% of the overall market capitalization of all U.S. corporate bond funds. We follow these 100 funds until the end of the observation period in December 2008 to avoid survivorship bias.[9] For each fund we obtain information on fund name, fund family, manager names, fund advisor name, TNA, turnover rate, fund classes, shares held by retail and institutional investors, fund fees, and the inception date from the CRSP mutual fund data base. We add information on the distribution of credit ratings and manager names from Morningstar Direct for each fund.

From the N-Q Forms we manually collect for each fund and each CDS position the notional value, the reference asset, and whether the swap was bought or sold.[10] This step generated information on 14,906 CDS positions. By far the largest top 100 U.S. corporate bond fund as of the second quarter of 2004 is the Total Return Fund of the PIMCO fund family with a TNA of $73 billion. The smallest fund is the Federated Strategic Income Fund by Federated Fixed Income Securities with a TNA of $1 billion. The most common Lipper fund classes among

---

[9] Two funds were discontinued and merged into other existing funds. Fidelity's Spartan Investment Grade Bond Fund was merged into the Investment Grade Bond Fund on July 28, 2006. The Oppenheimer High Yield Fund was merged into the Oppenheimer Champion Income Fund on October 12, 2006. Linnainmaa (2010) shows that mutual fund alphas estimated from a survivorship-bias-free data set are downward biased. Our results should not suffer from this "reverse survivorship bias" because the two funds that were merged during our observation period had above average alphas.

[10] To ease the extraction process from the raw txt and html files, we download the N-Q forms again from EdgarOnline, a subscription-based website, which already transforms the fund holdings into standard rft and pdf formats. We find 289 different N-Q forms that include at least one of these key words. However, in many cases, the CIK number refers to a family of funds rather than to one specific top-100 fund. We thus search for the top-100 fund names and exclude those N-Q forms that do not cover our top-100 funds. Additionally, we analyze right-censoring in the CDS holding history because this occurrence might be due to i) a change in the fund name; ii) a close of the respective fund; iii) a merger with another fund. In the last two cases the fund history ends while in the first case we employ the fund history. Since some fund families, in particular large ones such as Fidelity with 12 funds, contribute more than one fund, we are left with 379 N-Q form-fund observations from 65 top-100 funds with CDS data.

the top 100 funds are *high current yield funds* (32 funds) and *intermediate investment grade funds* (28 funds). *Corporate debt funds A-rated* and *investment grade, short-intermediate* feature 11 and 10 funds respectively. The remaining three fund classes, *short investment grade*, *corporate debt funds BBB-rated*, and *multi-sector income* consist of 6-7 funds each. Based on the correlation of fund returns between the Lipper fund classes we classify multi-sector income and high current yield funds as *high yield*, and all other funds as *investment grade*.[11]

To determine under- or overperformance, we obtain monthly fund returns from the CRSP mutual fund data base. We construct fund-based return benchmarks by calculating equally-weighted return indexes of all funds in each Lipper fund class.[12] For this exercise we use the universe of U.S. corporate bond funds, not just the largest 100 funds. These fund-based benchmarks allow us to determine the relative performance ranking of each of our 100 funds per fund category. Since funds may compare their performance not only to other bond funds, but to the returns of particular corporate bond classes, we also construct passive return benchmarks of corporate bonds that approximately reflect the asset allocation of our 100 funds. For this, we obtain Bank of America Merrill Lynch (BOFA ML) bond indexes from Datastream that match the risk profile of each one of the seven Lipper fund classes that occur in our sample. If a reasonable match cannot be found, we construct a new index from two or three bond indexes. The weighting scheme we use for this construction is based on Moody's credit rating distribution for U.S. corporate bonds during our observation period. See the appendix for further details.

---

[11] The correlations of semi-annual fund returns within investment grade and within high yield funds generally exceed 0.90. The correlations of fund returns between those two categories are usually well below 0.90.
[12] In robustness tests we also use value-weighted return indexes.

II Results

In this section we first describe the top 100 U.S. corporate bond funds in terms of fund size and other fund characteristics, the use of CDS and the four principal strategies among the top 100 bond funds. In particular, we demonstrate which CDS strategies tend to increase a fund's exposure to credit risk and which tend to hedge credit risk. In Section B, we examine whether the use of some CDS strategies could be motivated by fund tournament considerations.

A The Use of CDS by U.S. Corporate Bond Funds

Table I shows summary statistics for the top 100 bond funds. Not surprisingly, bond funds are large. The mean and median TNAs are $5 billion and $2 billion respectively. The dispersion in fund sizes is large and highly skewed. TNAs range from 264 million to over 130 billion. The reason why there appear to be a number of smaller funds among the top 100 is that some funds experienced significant value losses and redemptions during the financial crisis in 2008.[13] Note that the smallest of the top 100 funds in 2004 had a TNA of $1 billion.

[Table I about here]

The distributions of fund sizes of investment grade and high yield funds are roughly similar to the overall average, except that the ultra large funds, with TNAs above $15 billion, all belong to the group of investment grade funds. This fact affects the sample means, so that the mean TNA of investment grade funds is about twice the mean of high yield funds, while the remaining percentiles (except for the maximum) are roughly similar. The average fund age (since inception) among the top 100 bond funds is 21 years, ranging from as little as four years to 73 years. About 75% of the top 100 funds belong to a larger fund family, i.e., a fund family that has at least two funds among the top 100 corporate bond funds in its portfolio.[14] About 60% of funds are managed by a team of two or more fund managers. These figures are also similar for investment grade and high yield bonds. In contrast, however, there is a larger proportion of institutional investors among investment grade funds. On average, institutions hold 44% of the TNA of investment grade funds , while institutions hold only 16% of the TNA of high yield funds. Investment grade and high-yield funds also differ in terms of the average fraction of junk-rated bonds and the average credit rating, expressed as the average five-year cumulative default frequency. Investment grade funds invest on average only 4.9% of their TNAs in junk-rated bonds, while high-yield funds invest 80.1% of their TNAs in junk-rated bonds. Consistent with a riskier asset allocation, high yield funds maintain lower cash levels (6.5%) than investment grade funds (15.3%).

The total expense ratios of the top 100 funds are on average substantially lower for investment grade funds (0.61%) than for high yield funds (1.06%).[15] Consistent with Moneta (2011) we find relatively high asset turnover ratios among bond funds, suggesting active portfolio management is common among these funds. Furthermore, the turnover ratio of investment grade funds is with 1.79 more than twice the turnover ratio of high yield funds. Finally and perhaps surprisingly, we find that 50% of investment grade funds use CDS, while only 28% of high yield funds use CDS.

Figure 1 shows that the number of funds that held CDS positions tripled, from 21 in 2004 to 60 in 2008. In total there were 65 funds that used CDS sometime between 2004 and 2008,

---

[13] These redemptions were especially pronounced among high yield funds. At least 75% of these funds experienced fund outflows during the sample period, while the same can be said only for 25% of investment grade funds.
[14] This definition of a large fund family follows Koski and Pontiff (1999).
[15] Expense ratios, turnover ratios, and the fraction of retail investors are value-weighted averages over the outstanding fund classes.

while 35 funds never used CDS. Among the 65 CDS-using funds, 17 funds held CDS positions throughout our sample period.[16]

[Figure 1 about here]

Among funds that used CDS, the average total notional value of CDS positions increased from 2% of TNA in 2004 to 14% of TNA in 2008. The most significant increases in the size of CDS positions took place in 2007 and 2008. While most funds maintain modest CDS positions, some funds carried very large CDS positions relative to their TNAs. For example, at the end of the first half of 2007, the Oppenheimer Champion Income Fund had a TNA of $2.5 billion and CDS positions with a total notional value of $0.8 billion (33% of TNA). Until the end of 2008, the fund lost more than 50% of its TNA. While the size of the derivatives position was reduced nominally, it increased to 58% of TNA.

The available data allows us to distinguish between four general CDS strategies. Funds can buy or sell CDS, and these CDS can be written on a single reference asset such as a corporate bond (single-name CDS), or on a portfolio of bonds, or a CDS index (multi-name CDS).[17] Obviously, each CDS position can be motivated by idiosyncratic market views about credit spreads, which are unobservable to us. In addition, there can by systematic differences in the motivations for the four CDS strategies. When funds buy CDS they buy credit protection, and thus reduce their credit exposure if the reference asset is part of the fund's holdings. When they sell CDS they sell credit protection, which increases the fund's credit exposure ceteris paribus. In addition, single-name CDS can be used to create a synthetic corporate bond, which can at times

---

[16] Mutual funds should be preferred counterparties due to the high transparency of a fund's assets, which makes the evaluation of counterparty risk relatively easy, and the unlikely possibility that mutual fund managers possess valuable private information with respect to future credit spreads.

[17] CDS positions are defined as multi-name if the reference asset of a CDS position includes at least one of the following key words: ABX, CDX, iBoxx, iTraxx, CMBS, CMBX, Trust, backed.

provide higher expected returns than the cash bond. To create a synthetic corporate bond a fund would sell a single-name CDS and invest the notional value in a risk-free security. Another CDS strategy is known as a negative basis trade. In this case a fund purchases a corporate bond and purchases a CDS on the same bond. Such trade would yield a positive cash flow if the spread of the bond is higher than the spread of the CDS (negative basis) and if the swap counterparty does not default. Of course, a negative basis trade is subject to counterparty and liquidity risk, which may partially explain the lower CDS spread. This example shows how using CDS can expose mutual fund investors to new, possibly unexpected risks.

In general, long CDS positions tend to decrease a fund's credit risk exposure, while short positions tend to increase a fund's credit risk exposure and potentially increase a fund's implicit leverage. The high liquidity of many multi-name CDS should also make them preferred risk-shifting tools in the absence of a market view on particular reference names. In addition, multi-name CDS are subject to less idiosyncratic risk than single-name CDS. We therefore expect that risk-shifting due to tournament behavior is implemented foremost by selling multi-name CDS.

Table II provides descriptive statistics of each CDS strategy. The largest positions are generally multi-name CDS. On average they represent 4-5% of a fund's TNA, while single-name CDS represent only 2-3% of TNA.[18] Both multi- and single-name CDS positions are on average short. However, multi-name CDS positions exhibit more volatility than single-name CDS positions, which are net short in each period during our sample period, while multi-name positions switch between being net short and net long several times. This volatility suggests that multi-name CDS may be used for position taking rather than for hedging purposes. Thus, during

[18] We code the notional amounts of long positions positive and those of short positions as negative.

our sample period mutual funds appear to use CDS to increase rather than to hedge their credit risk exposures on average.

[Table II about here]

Figure 2 shows histograms of the multi- and single-name CDS net positions scaled by TNA. Note that the horizontal axis displays the lower interval limits of each observation bucket, i.e., the “0.00” bucket contains the observations from the interval [0, 0.02). The two histograms confirm that for both single- and multi-name CDS, net short positions are more common than net long positions (all means and medians are negative). However, there clearly are large dispersions in the net CDS positions among the top 100 funds. Some have significant net short positions while others have significant net long positions even exceeding a fund’s TNA.

[Figure 2 about here]

To summarize, by 2008, the majority of the top 100 U.S. corporate bond funds were holding significant CDS positions on average. Bond funds are on average net sellers of CDS, which implies that funds use CDS to increase rather than to hedge their exposure to credit risk. Multi-name CDS positions represent the major strategies, being on average twice as large as single-name CDS positions. The volatility in multi-name CDS positions suggests that managers are timing credit markets using multi-name CDS.

B CDS Strategies and Tournaments

In this section we first examine which funds / fund managers are more likely to use CDS, in order to compare our results to the existing literature on derivatives usage by mutual funds. Second, we examine whether funds increase their credit risk exposures by selling multi-name CDS in response to poor fund performance.

The prior literature has shown that the use of derivatives by mutual funds is related to fund size, asset turnover, membership in a fund family, fund age, and fund expenses. We follow this literature and estimate logit models based on all 100 funds in our sample. We further control our regressions for the fraction of a fund's TNA held by institutional investors because institutional investors may influence a fund manager regarding CDS usage, while it is unlikely that retail investors have any direct impact on a fund's derivatives strategy. We distinguish between team-managed and single-manager funds because Almazan, Brown, Carlson and Chapman (2004) find that more constraints to use derivatives are placed on funds that are managed by a team rather than a single manager. We also include fund flows as an additional control variable because managers may hold CDS as a response to short-term money flows as it is often cheaper to trade CDS than to trade corporate bonds. Finally, we distinguish between investment grade and high yield funds, and include dummy variables for each time period to control for common time effects.

Table III reports the marginal effects from pooled logit models (Columns I and II), and random-effects logit models (Columns III and IV). For each specification we estimate a second regression excluding observations from the second half of 2008, which witnessed unprecedented market dislocations due to the collapse of Lehman Brothers. Consistent with Koski and Pontiff (1999), we find that the use of CDS is positively correlated with membership in a larger fund family and with asset turnover. If a fund belongs to a large fund family it is about 30% more likely to use CDS than funds that do not belong to a large fund family. This can be due to economies of scale if the costs of setting up a CDS trading desk can be shared across several funds. For example, Deli and Varma (2002) find that funds with the highest transaction cost benefits are more likely to permit investments in derivatives. An increase in the asset turnover ratio by one standard deviation increases the likelihood to use CDS by about 10%. Some authors have interpreted the asset turnover as a proxy for how actively a fund is managed. The positive correlation between asset turnover and CDS usage suggests that CDS are especially useful tools for active fund managers, possibly due to their generally lower trading costs compared to corporate bonds. This interpretation would also be consistent with our earlier conclusion that CDS are used to take risks rather than to passively hedge risks.

[Table III about here]

In contrast to earlier studies, however, we find no size effect in our sample, probably because we focus on the largest 100 bond funds. Had we included smaller funds in our analysis, we might have found a positive correlation between fund size and CDS usage. Consistent with the univariate results, we find that investment grade funds are about 20% more likely to use CDS than high yield funds. This result may have several causes. First, it could be a pure supply effect as CDS on investment grade debt tend to be more liquid than CDS on high yield debt. Second, it could be that investment grade funds have stronger incentives for risk-shifting strategies using CDS than high yield funds. The returns of investment grade funds tend to be more clustered than the returns of high yield funds. Thus, a relatively small performance improvement could affect the relative performance ranking of investment grade funds, while the same performance improvement may be insufficient to affect the relative ranking of high yield funds. An argument against a pure supply effect is that investment grade funds engage in riskier CDS than indicated by their general asset allocations. The average fraction of junk-rated CDS reference names is 14.9%, while their average fraction of junk-rated corporate bonds is only 4.9%. In contrast, high-yield funds show a lower proportion of junk-rated CDS reference names (64%) compared to their junk-rated bond positions (80.1%), on average. Thus, investment grade funds are not only more likely to use CDS, but that they are also more prone to invest into riskier reference names.

Consistent with Almazan, Brown, Carlson and Chapman (2004), we find that funds that are managed by a single manager are about 16% more likely to use CDS than funds managed by a team. These findings are also in line with Chevalier and Ellison (1997), who argue that single fund managers have more of their own reputation at risk and therefore need less investment constrains compared to team-managed funds.

Next, we examine whether some of the CDS strategies are motivated by a desire to increase total fund risk following poor past performance as suggested by the tournament literature. For example, the Oppenheimer Champion Income Fund is involved in a class action suit, in which the fund's investors allege that the fund "altered its investment style and began to significantly increase its risk in the hopes of seeking higher returns, including by dramatically increasing its use of derivative instruments." Applying this idea to the use of CDS, we expect that funds with below average midyear performance subsequently increase their CDS short positions. Given that multi-name CDS are less subject to idiosyncratic risks, and that they tend to be more liquid than single-name CDS, we expect multi-name CDS to be the preferred instrument to increase fund risk. As explained above, the other three CDS strategies may follow different rationales such as hedging, synthetic bond investments or negative basis trades. For completeness, however, we perform our tournament tests on all four CDS strategies.

In order to test the risk-shifting hypothesis we proceed in two steps. First, we estimate fund flow – performance sensitivities following Sirri and Tufano (1998) to determine whether there are risk-shifting incentives that could lead to fund tournaments among corporate bond funds. Following Chevalier and Ellison (1997), we test in a second step whether funds' CDS strategies respond to their past performance.

We estimate the fund flow – performance sensitivities by estimating the following model using annual data of all corporate bond mutual funds listed in CRSP between 1964 and 2009.

$$Fund\ flow_{it+1} = \alpha + \beta_1 Raw\ return_{it} + \beta_2 Raw\ return_{it}^2 + \delta Controls_{it} + \gamma_t + e_{it} \quad (1)$$

As control variables we include the standard deviation of monthly returns as a measure of fund risk, fund size, and the total expense ratio, where δ denotes the vector of coefficients for these controls. Table IV reports the estimation results of equation (1) using the Fama-McBeth approach (without the time fixed effects γ_t) and a standard pooled OLS regression. Consistent with Sirri and Tufano (1998) and Gutierrez, Maxwell, and Xu (2009), we find a convex relation between fund flows and a fund's past performance using either estimation method. This convex relation is robust to controlling for fund risk, fund size, and fund trading costs. These results imply that bond fund investors tend to allocate new capital to the best performing funds, while they withdraw money from less well performing funds underproportionally. This convexity gives underperforming managers an incentive to increase total fund risk.

[Table IV about here]

Following Chevalier and Ellison (1997), we then test in a second step whether funds' CDS strategies respond to their past performance by estimating the following specification for each of the four CDS strategies.

$$\Delta \frac{CDS\ notional\ amount_{it}}{NAV_{it}} = \alpha + \beta_1 Performance_{it-1} + \beta_2 Fund\ flow_t + \gamma_t + e_{it} \quad (2)$$

The dependent variable measures the change in a fund's CDS positions during the second half of a calendar year, while *Performance* measures fund performance during the first half of a calendar year. We use two variables to measure the performance of a fund. The first measure is defined as the difference between a fund's total return and the return of our fund-based benchmark. The second measure is defined as the difference between a fund's total return and the return of the passive benchmark. Since short CDS positions are coded negatively, we expect a positive coefficient on past performance ($\beta_1 > 0$) for short positions.

Fund managers may also adjust their CDS positions due to their market expectations. Since credit spreads have been shown to be mean-reverting (Bhanot, 2005) there could be industry-wide adjustments in funds' CDS positions: Fund managers buy credit protection when the market expects credit spreads to increase and sell credit protection when the market expects credit spreads to decrease. To control our analysis for this effect we include time fixed-effects in all regressions. Finally, short CDS positions may respond to new fund inflows. For example, fund managers may temporarily employ CDS to adjust a fund's duration, which had changed as a result of new net inflows. We calculate net fund flows following Sirri and Tufano (1998), and include this as an additional control variable.

Table V reports the estimation results of equation (2) using a Heckman selection model.[19] In the first stage we model the decision to use CDS as in Table III. The exclusion restrictions are fund size, asset turnover ratio, fund age, big fund family dummy, total expense ratio, investment grade dummy, and the fraction of retail investors.[20] Since the first stage results are similar to the results reported in Table III, we omit them in Table V. In the second stage, we use past performance and fund flows as the only regressors (besides time fixed effects) because the regressors of the first stage are relatively stable over time and do not explain changes in any of the four CDS strategies.

[Table V about here]

[19] We obtain qualitatively similar results if we estimate standard OLS regressions, which are available upon request.

The results show that changes in short, multi-name CDS positions are significantly correlated with past performance. A decrease in the relative performance by 50 bp increases the size of the short, multi-name CDS positions by 0.9-1.3 % (relative to TNA). Given that short, multi-name positions average at about 4.6% of TNA, this is an economically large increase. Thus, fund managers sell more multi-name CDS following poor performance. When we compare fund performance during the second half of a calendar year with changes in CDS positions during the first half of the following year we find no significant relationships. This suggests that the risk-shifting we observe is motivated by fund tournaments.

As expected, fund managers do not systematically adjust their long, multi-name or their single-name CDS positions following poor performance. This is consistent with the view that these CDS positions follow different rationales and are not used to increase the riskiness of a fund due to tournament incentives. Finally, we find no evidence that fund flows drive changes in CDS positions. Thus, while fund managers may use CDS to quickly respond to fund flows, this effect is not present on a semi-annual basis.[21]

[Table VI about here]

In Table VI, we allocate each fund to one of five relative performance quintiles based on the first half-year performance and examine the change in the short, multi-name CDS positions during the second half of the same year. The results show that it is predominantly firms in the lowest performance quintile (using either benchmark), which increase their short, multi-name CDS positions by 3.5% of TNA in the second half of a calendar year. The effect is both

---

[20] We test the validity of our exclusion restrictions and find that the asset turnover ratio, fund age, and the big fund family dummy have a significant selection effect in the first stage (see Table III); and that the exclusion restrictions are uncorrelated with the error terms from the second stage (not reported).

statistically and economically significant, given that the short, multi-name CDS positions average at 4.7%.[22] There is some weaker evidence that top-performing funds also engage in some risk-shifting using CDS. Funds that significantly outperform their respective passive performance benchmarks increase their short, multi-name CDS positions by 2.7% of TNA on average. In fact, a Wald test shows that the coefficients of Quintile 1 and 5 do not differ in a statistical sense (see Column 2). The average changes in the short, multi-name CDS positions for the five performance quintiles are also shown in Figure 3. It is apparent that any risk-shifting using multi-name CDS takes place among funds in the bottom and possibly also the top performance quintiles.

[Figure 3 about here]

Chevalier and Ellison (1997) show that tournament behavior is concentrated among younger funds, which still need to build their reputations. We therefore check whether the risk-shifting we observe is concentrated among the younger funds in our sample. For this purpose we create a dummy variable, which equals one if a fund's age is below the median fund age and zero otherwise, and interact this dummy variable with a fund's past performance. The results, shown in the first two columns of Table VII, confirm that the evidence of risk-shifting using short multi-name CDS is concentrated among the younger funds. It is possible that younger funds are more actively managed and therefore exhibit higher asset turnovers. We therefore also interact a fund's past performance with a dummy variable, which equals one if a fund exhibits above median asset turnover and zero otherwise. Indeed, we find that funds with higher asset turnovers are more prone to increasing their short, multi-name CDS positions if they experience underperformance

[21] One might argue that the fund flow variable induces a reverse causality problem: higher risk levels correspond to higher expected returns, which yield higher inflows. We thus re-run the Heckman models without the fund flow variable. Unreported results show qualitatively unchanged results.

[22] In unreported regressions we find that this effect is especially strong for investment grade funds.

during the first half of a calendar year. In fact, this effect seems to be even more important than fund age in explaining risk-shifting, since the *Young fund* coefficient becomes smaller (and even insignificant in Column 4). Given that we find a positive relation between being a younger fund and more active trading, both variables point into the same direction: Younger funds have less too lose than more established funds and show more pronounced risk-shifting in short, multi-name CDS strategies.

[Table VII about here]

As mentioned in the introduction, fund managers have a variety of strategies available to them to increase the riskiness of their funds. Apart from using derivatives, they could shift their holdings towards bonds with higher credit risks such as junk bonds. Alternatively, they could decrease their cash holdings, or increase their trading activities. We therefore examine whether managers use any of these risk-shifting strategies in response to poor performance to complement their derivatives strategies. We use two variables to measure changes in funds' asset allocations: the average 5-year cumulative default frequency of a fund's bond holdings and the share of junk-rated bonds relative to investment grade bonds. Cash holdings are measured by the value of cash relative to a fund's TNA, while we use a fund's asset turnover to proxy for its trading activities.

[Table VIII about here]

The results in Table VIII show that those corporate bond funds that use CDS do not systematically increase risk following poor performance using any of the alternative strategies. Underperforming funds do shift towards riskier assets, but the effect is not statistically significant. Similarly, cash holdings decline following poor performance, even after controlling for fund flows, but the effect is again not statistically significant. If anything, underperforming funds reduce their trading activities, possibly to reduce trading costs. We also examined the correlations between changes in CDS positions and changes in asset compositions. Consistent with the multi-variate results in Table VII we find that when firms increase their short, multi-name CDS positions they also shift towards riskier asset allocations, but the correlations are not statistically significant.

We perform several robustness tests for short, multi-name CDS strategies, which we report in Table IX. First, we drop those funds that experienced a management change in the second half of a calendar year. Obviously, a new management team may have different risk preferences from an old team, especially if the new team replaces the old team following poor performance. This restriction reduces the sample size by 15 uncensored observations, but does not affect the results in any material sense. If anything, the results are even more pronounced (see Columns I and II).

[Table IX about here]

To ensure that our results are not driven by changes in TNAs rather than changes in the CDS positions, we re-estimate all regressions using *Δ CDS notional amount* as the dependent variable. As before, the coefficients on the performance variables are highly significant, implying that it is the size of the CDS position that is adjusted following poor performance (see Columns III and IV).

Third, we replace the excess return calculated from an equally-weighted fund-based benchmark with the excess return calculated from a value-weighted fund-based benchmark. Again, the results are not affected by this change (see Column V).

Finally, we estimate equation (2) using a seemingly unrelated regression (SUR) model in order to take potential correlation among residuals of the four different CDS strategies into account. Again, the results remain qualitatively unchanged (see Columns VI and VII).

To summarize, we find that funds that underperform during the first half of a calendar year increase their short, multi-name CDS positions during the second half of the same calendar year. This effect is both statistically and economically significant, and concentrated among funds in the lowest performance quintile, younger funds and more actively managed funds. When we compare a fund's underperformance during the second half of a calendar year with changes in the fund's CDS positions during the first half of the *next* fiscal year, we find no significant correlations. These findings are consistent with risk-shifting due to fund tournament behavior as first proposed by Brown, Harlow, and Starks (1996).

III Conclusion

In this paper we analyze the use of credit default swaps by the top 100 U.S. corporate bond funds between 2004 and 2008. We find that the use of CDS has increased from about 20% of funds in 2004 to 60% of funds in 2008. The size of CDS positions (measured by their notional values) is usually less than 10% of a fund's TNA, but some funds exceed this level by a wide margin, especially during the financial crisis in 2008. Overall, funds are net sellers of CDS, which shows that fund managers use CDS to take on credit risk rather than to hedge credit risk. The relatively high volatility of the size of CDS positions further suggests that CDS are used for market-timing rather than hedging considerations.

Consistent with the tournament hypothesis advanced by Brown, Harlow, and Starks (1996), we find that underperforming funds tend to increase fund risk by increasing their short, multi-name CDS positions. This effect is concentrated among younger and more actively managed funds. Derivatives should be the instrument of choice for risk-shifting due to their higher liquidity and thus lower trading costs compared to many corporate bonds. In fact, we find no evidence of risk-shifting through changes of a fund's asset composition or changes in a fund's trading behavior. Our results have practical implications for investors, because Huang, Sialm, and Zhang (2010) find that funds engaging in risk-shifting perform worse than funds that keep stable risk levels over time.

References

Almazan, A, K.C. Brown, M. Carlson, and D.A. Chapman, 2004, Why Constrain Your Mutual Fund Manager? *Journal of Financial Economics* 73, 289-321.

Aragon, G.O., and V. Nanda, 2010, On Tournament Behavior in Hedge Funds: High-water Marks, Manager Horizon, and the Backfilling Bias, *Review of Financial Studies*, forthcoming.

Bhanot, K., 2005, What Causes Mean Reversion in Corporate Bond Index Spreads? The Impact of Survival, *Journal of Banking and Finance* 29, 1385-1403.

Brown, K., W. Harlow, and L. Starks, 1996, Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry, *Journal of Finance* 51, 85-110.

Chen, H.-L., and G.G. Pennacchi, 2009, Does Prior Performance Affect a Mutual Fund's Choice of Risk? Theory and Further Empirical Evidence, *Journal of Financial and Quantitative Analysis* 44, 745-775.

Chevalier, J., and G. Ellison, 1997, Risk Taking by Mutual Funds as a Response to Incentives, *Journal of Political Economy* 105, 1167-1200.

Clifford, C.P., J.A. Fulkerson, B.D. Jordan, and S.R. Waldman, 2010, Do Investors Care about Risk? Evidence from Mutual Fund Flows, University of Kentucky working paper.

Deli, D.N., and R. Varma, 2002, Contracting in the Investment Management Industry: Evidence From Mutual Funds, *Journal of Financial Economics* 63, 79-98.

Elton, E.J., M.J. Gruber, and C.R. Blake, 2003, Incentive Fees and Mutual Funds, *Journal of Finance* 58, 779-804.

Gutierrez, R.C., W.F. Maxwell, and D. Xu, 2009, On Economies of Scale and Persistent Performance in Corporate-Bond Mutual Funds, working paper.

Hirtle, B., 2009, Credit Derivatives and Bank Credit Supply, *Journal of Financial Intermediation* 18, 125-150.

Hu, P., J.R. Kale, M. Pagani, and A. Subramanian, 2011, Fund Flows, Performance, Managerial Career Concerns, and Risk-Taking, *Management Science* 57,628-646.

Huang, J., C. Sialm, and H. Zhang, 2011, Risk Shifting and Mutual Fund Performance, *Review of Financial Studies* 24, 2575-2616.

Johnson, L.D., and W. Yu, 2004, An Analysis of the Use of Derivatives by the Canadian Mutual Fund Industry, *Journal of International Money and Finance* 23, 947-970.

Kempf, A., and S. Ruenzi, 2008, Tournaments in Mutual-Fund Families, *Review of Financial Studies* 21, 1013-1036.

Kempf, A., S. Ruenzi, and T. Thiele, 2009, Employment Risk, Compensation Incentives and Managerial Risk Taking - Evidence from the Mutual Fund Industry, *Journal of Financial Economics* 92, 92-108.

Koski, J.L., and J. Pontiff, 1999, How Are Derivatives Used? Evidence from the Mutual Fund Industry, *Journal of Finance* 54, 791-816.

Linnainmaa, J.T., 2010, Reverse Survivorship Bias, Chicago Booth working paper.

Mahieu, R., and Y. Xu, 2007, Hedging With Interest Rate and Credit Derivatives by Banks, RSM Erasmus University working paper.

Marin, J.M., and T. Rangel, 2006, The Use of Derivatives in the Spanish Mutual Fund Industry, UPF Department of Economics and Business working paper.

Moneta, F., 2011, Measuring Bond Mutual Fund Performance with Portfolio Characteristics, working paper.

Minton, B.A., R.M. Stulz, and R.G. Williamson, 2009, How Much Do Banks Use Credit Derivatives to Hedge Loans? *Journal of Financial Services Research* 35, 1-31.

Schwarz, C.G., 2011, Mutual Fund Tournaments: The Sorting Bias and New Evidence, *Review of Financial Studies*, forthcoming.

Sirri, E.R., and P. Tufano, 1998, Costly Search and Mutual Fund Flows, *Journal of Finance* 53, 1589-1622.

Van Ofwegen, R., W.F.C. Verschoor, and R.C.J. Zwinkels, 2010, The Effect of Credit Derivatives on Financial Sector Stability, Erasmus School of Economics working paper.

Figure 1: Number of CDS Users and the Size of the Total CDS Position Among the 100 Largest U.S. Corporate Bond Funds

The figure shows the number of CDS users (left Y-axis) and the size of the total CDS positions (right Y-axis) among the corporate bond funds. The sample is comprised of the largest (by TNA) 100 U.S. mutual corporate bond funds as of the end of the second quarter of 2004 as reported by the CRSP survivorship-free mutual fund data base. The reporting period is semi-annual, 2004 – 2008. The size of the CDS positions is measured by the sum of the notional amount of the CDS positions over a fund's size TNA.

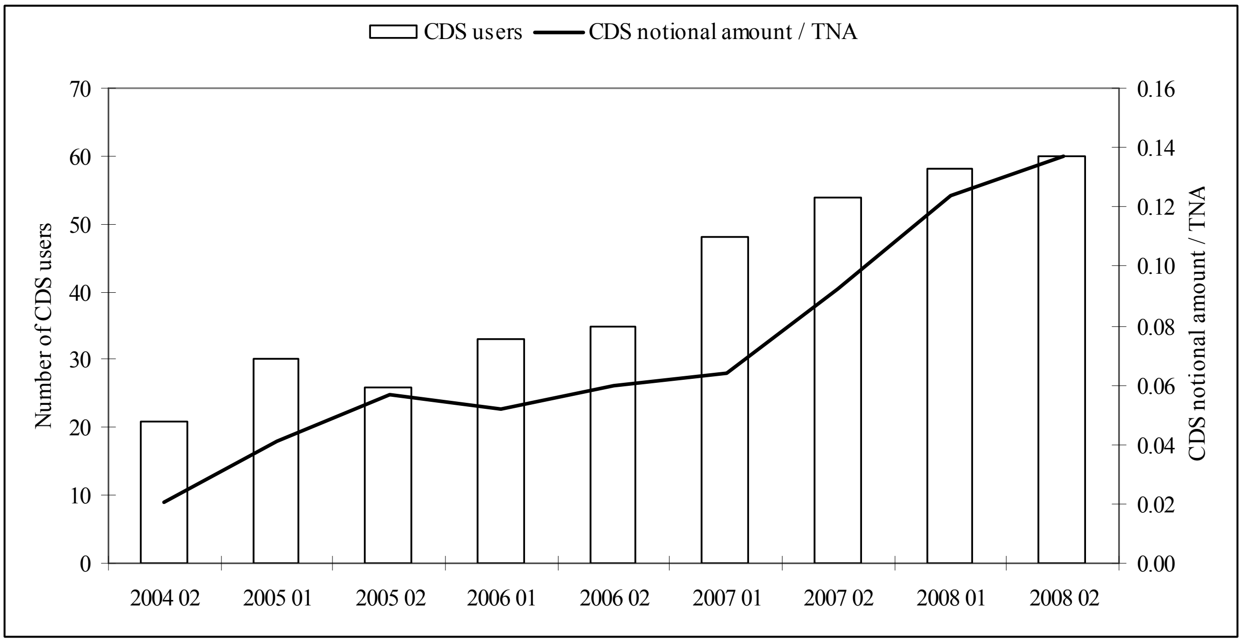

Figure 2: The Distribution of Net Notional Amounts of CDS Positions

These figures show the distribution of the net notional amounts (protection bought – protection sold) of multi-name and single-name CDS scaled by a fund's TNA. The horizontal axis displays the lower interval limits of each observation bucket, i.e., the "0.00" bucket contains the observations from the interval [0, 0.02) and thus contains zero and positive net notional values.

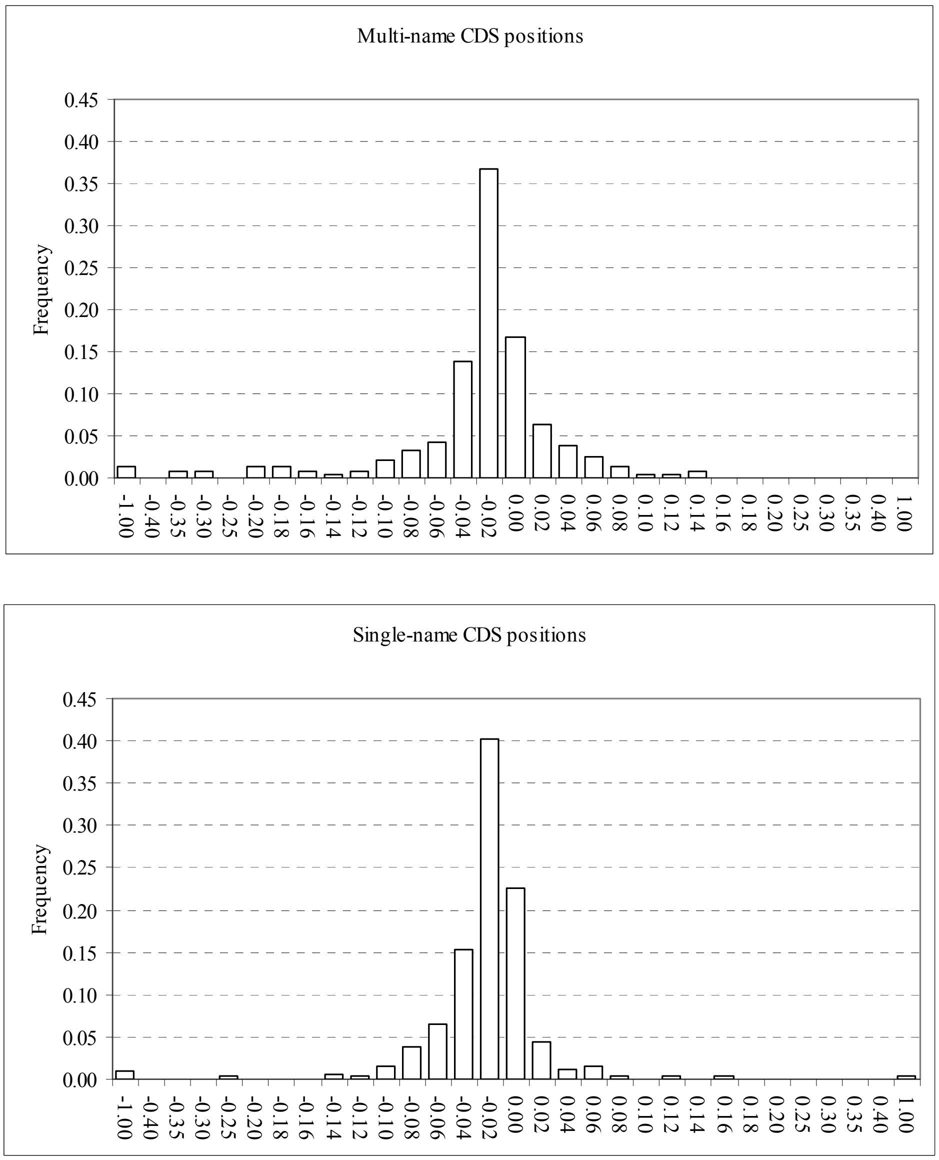

Figure 3: Changes in Short, Multi-Name CDS Positions

The figure shows the average change in the short, multi-name CDS positions, measured by the CDS notional values over a fund's TNA, during the second half of a calendar year for five performance quintiles based on the fund performance during the first half of a calendar year. Two benchmarks are used to determine a fund's excess performance: a fund-based and a passive benchmark (see the appendix for further details).

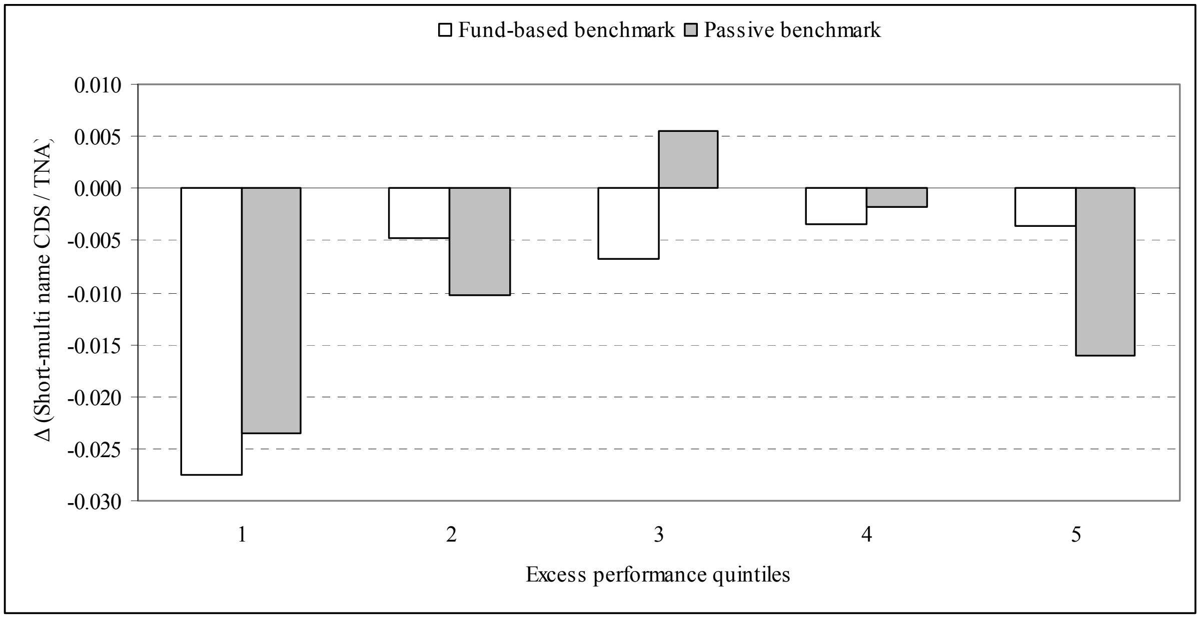

Table I: Fund Characteristics

This table shows fund characteristics of the top 100 U.S. mutual corporate bond funds between 2004 and 2008. The top 100 funds are defined as the largest (by TNA) 100 corporate bond funds in the CRSP survivorship-free mutual fund data base as of the end of the second quarter of 2004. We define a fund as a corporate bond fund if it belongs to one of the following Lipper fund classes: Corporate Debt Funds (A-Rated), Corporate Debt Funds (BBB-Rated), Intermediate Investment Grade Debt Funds, Short Investment Grade Debt Funds, Short-Intermediate Investment Grade Debt Funds, Multi-Sector Income Funds, and High Current Yield Funds. Funds in the last two fund classes are classified as high yield funds. Otherwise, we refer to funds as investment grade funds. *Fund age* measures the number of years since a fund's inception. *Big fund family* is a dummy variable that equals 1 if another fund in our sample belongs to the same fund family and 0 otherwise. *Fraction of institutional investors* is the proportion of a fund's TNA held by institutional investors (net assets of institutional investor fund classes / TNA). The *asset turnover ratio* is defined as the minimum of aggregated sales and purchases of securities divided by the 12-month average TNA. *Total expense ratio* is the sum of a fund's operating expenses (including 12b-1 fees, waivers and reimbursements) over a fund's TNA. *Team managed* is a dummy variable that equals 1 if the fund is managed by two or more managers and 0 otherwise. *Fund flow* is measured by $(TNA_t - TNA_{t-1}(1 + \text{semi-annual return}_t))/TNA_{t-1}$. *CDS usage* is a dummy variable if a fund uses CDS and zero otherwise. All data are taken from the CRPS survivorship free mutual fund data base. We furthermore use Morningstar Direct and Moody's annual default reports (for the default rates) as additional data source. We measure the funds' bond portfolios by weighting their bonds according to the bonds' credit ratings. We weight the ratings by the average, cumulative 5-year default frequency (*Average 5-year default frequency*) and the share of junk rated (below BBB-) bonds (*Proportion of junk-rated debt*). *Net cash ratio* is the net cash (cash minus liabilities) over a fund's TNA.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Panel A: All funds								
TNA (in $ millions)	890	5,040	11,502	264	1,274	2,155	5,061	130,930
Fund age (years)	890	21	10	4	13	19	28	73
Big fund family (dummy)	890	0.747	0.435	0.000	0.000	1.000	1.000	1.000
Fraction of institutional investors	890	0.335	0.400	0.000	0.000	0.089	0.810	1.000
Asset turnover ratio	890	1.356	1.418	0.000	0.480	0.810	1.735	10.810
Total expense ratio (% p.a.)	890	0.784	0.348	0.127	0.550	0.746	1.072	1.755
Team managed (dummy)	890	0.594	0.491	0.000	0.000	1.000	1.000	1.000
Fund flow (semi-annual)	890	-0.011	0.116	-0.355	-0.084	-0.023	0.051	0.367
CDS usage (dummy)	890	0.410	0.492	0.000	0.000	0.000	1.000	1.000
Average 5-year default frequency	710	0.072	0.078	0.002	0.009	0.020	0.157	0.281
Proportion of junk-rated debt	710	0.343	0.393	0.000	0.015	0.082	0.858	0.994
Net cash ratio	863	0.119	0.137	-0.151	0.034	0.078	0.153	0.679
Panel B: Investment grade funds								
TNA (in $ millions)	544	6,309	14,415	264	1,385	2,374	5,399	130,930
Fund age (years)	544	20	9	6	14	18	26	54
Big fund family (dummy)	544	0.752	0.432	0.000	1.000	1.000	1.000	1.000
Fraction of institutional investors	544	0.444	0.427	0.000	0.000	0.357	0.929	1.000
Asset turnover ratio	544	1.793	1.648	0.000	0.590	1.315	2.523	10.810
Total expense ratio (% p.a.)	544	0.609	0.267	0.127	0.480	0.600	0.730	1.419
Team managed (dummy)	544	0.581	0.494	0.000	0.000	1.000	1.000	1.000
Fund flow (semi-annual)	544	0.010	0.123	-0.355	-0.060	0.002	0.072	0.367
CDS usage (dummy)	544	0.496	0.500	0.000	0.000	0.000	1.000	1.000
Average 5-year default frequency	435	0.014	0.013	0.002	0.006	0.011	0.017	0.091
Proportion of junk-rated debt	435	0.049	0.063	0.000	0.005	0.028	0.065	0.387
Net cash ratio	526	0.153	0.161	-0.151	0.041	0.105	0.212	0.679

Continued Table I:

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Panel C: High yield funds								
TNA (in $ millions)	346	3,044	2,704	388	1,120	1,882	4,395	13,400
Fund age (years)	346	22	12	4	13	20	28	73
Big fund family (dummy)	346	0.740	0.439	0.000	0.000	1.000	1.000	1.000
Fraction of institutional investors	346	0.164	0.278	0.000	0.001	0.037	0.152	1.000
Asset turnover ratio	346	0.668	0.361	0.000	0.410	0.580	0.830	2.020
Total expense ratio (% p.a.)	346	1.059	0.275	0.179	0.860	1.101	1.216	1.755
Team managed (dummy)	346	0.616	0.487	0.000	0.000	1.000	1.000	1.000
Fund flow (semi-annual)	346	-0.043	0.098	-0.355	-0.106	-0.055	-0.001	0.367
CDS usage (dummy)	346	0.275	0.447	0.000	0.000	0.000	1.000	1.000
Average 5-year default frequency	275	0.162	0.045	0.033	0.141	0.173	0.191	0.281
Proportion of junk-rated debt	275	0.808	0.197	0.175	0.760	0.886	0.935	0.994
Net cash ratio	337	0.065	0.057	-0.151	0.030	0.050	0.091	0.409

Table II: The CDS Strategies

The table reports the notional amounts of CDS positions relative to a fund's TNA for each of the four primary CDS strategies separately (CDS users only). Columns 5 and 6 also report the net notional amounts over TNA. The netting is done per fund-period and separately for multi- and single-name CDS positions. The last column reports the net notional amounts over TNA for multi- and single-name CDS lumped together.

	CDS notional amount / TNA				CDS net notional amount / TNA		CDS net notional amount / TNA
	Multi-name		Single-name				
Period	Long	Short	Long	Short	Multi-name	Single-name	
2004 02	0.074	-0.014	0.011	-0.010	0.011	-0.006	-0.002
2005 01	0.023	-0.036	0.013	-0.018	-0.026	-0.013	-0.026
2005 02	0.037	-0.042	0.014	-0.020	-0.019	-0.012	-0.023
2006 01	0.035	-0.031	0.018	-0.018	0.000	-0.008	-0.007
2006 02	0.053	-0.027	0.024	-0.024	0.010	-0.007	-0.001
2007 01	0.036	-0.030	0.016	-0.031	0.001	-0.014	-0.012
2007 02	0.035	-0.053	0.019	-0.040	-0.023	-0.019	-0.035
2008 01	0.069	-0.086	0.019	-0.047	-0.051	-0.027	-0.059
2008 02	0.061	-0.093	0.044	-0.036	-0.039	-0.000	-0.026
2004 02-2008 02	**0.047**	**-0.046**	**0.020**	**-0.027**	**-0.015**	**-0.012**	**-0.021**

Table III: The Determinants of CDS Usage

This table reports the marginal effects of logit regressions. The dependent variable is a dummy variable that equals 1 if a fund used CDS during a semi-annual period and zero otherwise. The sample period is 2004 – 2008 and the sample frequency is semi-annual. *Investment grade* is a dummy variable that equals 1 for investment grade funds and 0 for high yield funds. The definitions of all other independent variables can be found in Table I. Standard errors are reported in parentheses. For models I and II we report standard errors clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	CDS dummy$_t$			
Variables	I	II	III	IV
ln(TNA)	0.0315	0.0639	-0.0466	0.0174
	(0.0534)	(0.0568)	(0.0657)	(0.0573)
Asset turnover ratio	0.0707	0.0729*	0.1024***	0.0942***
	(0.0460)	(0.0418)	(0.0546)	(0.0538)
ln(fund age)	0.1573	0.1255	0.2878*	0.1607
	(0.0996)	(0.0951)	(0.2050)	(0.1505)
Big fund family (dummy)	0.2829***	0.2732***	0.3117***	0.2570***
	(0.0863)	(0.0834)	(0.1558)	(0.1414)
Total expense ratio	0.1637	0.1668	-0.0499	0.0143
	(0.2012)	(0.1899)	(0.2851)	(0.2328)
Investment grade (dummy)	0.2005*	0.1933*	0.2801*	0.2394*
	(0.1084)	(0.1050)	(0.1911)	(0.1746)
Fraction of institutional investors	0.2345*	0.2104*	0.2705**	0.1064
	(0.1219)	(0.1142)	(0.1719)	(0.1283)
Team managed (dummy)	-0.1582*	-0.1614*	-0.2196**	-0.1569**
	(0.0910)	(0.0908)	(0.1355)	(0.1121)
Fund flows	-0.2564	-0.3632	0.0165	-0.0954
	(0.2722)	(0.3211)	(0.2172)	(0.1980)
Pooled Logit	Yes	Yes	No	No
Random-effects	No	No	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
2008 (second half) included	Yes	No	Yes	No
R square	0.1784	0.1735	0.4009	0.3719
N	890	792	890	792

Table IV: The Impact of Past Performance on Fund Flows

This table reports the impact of past performance on the growth of funds. We use a comprehensive sample of all corporate mutual funds from the CRPS survivorship-free mutual fund database covering 1964 to 2009. We also use the year 1963 to calculate lagged variables. We keep funds of the fixed income category (if this classification is available) and funds (if this classification is not yet available) that invest at least 85% in bonds and cash. We drop funds with "Equity", "Municipal", "Tax", "Treasury", "Government", and "Mortgage" in their fund name. We use the fund flow of year t+1 and regress it on the raw return of year t, the squared raw returns, the standard deviation of the twelve monthly returns of year t (*Risk*), the natural logarithm of the fund's TNA during year t (In(*TNA*)), and the sum of a fund's operating expenses (including 12b-1 fees, waivers and reimbursements) over a fund's *TNA* (*Total expense ratio*). Standard errors are reported in parentheses. The results in Column I are the mean coefficients of year-by-year regression runs following the Fama-McBeth approach. We use standard t-tests to obtain standard errors and significance levels. The results in Column II are from a pooled OLS regression with year fixed effects and standard errors that are clustered by year. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Fund $flow_{t+1}$	
Variable	I	II
Intercept	0.5894***	0.4418***
	(0.1144)	(0.0589)
Raw $return_t$	0.7064	0.5675***
	(0.5562)	(0.1934)
Raw return $squared_t$	3.5943*	0.4206*
	(1.9733)	(0.2093)
Std. dev. of raw $returns_t$	-2.1084***	-0.5806
	(0.6196)	(0.3751)
ln(TNA_t)	-0.0696***	-0.0771***
	(0.0141)	(0.0098)
Total expense $ratio_t$	0.0013	-0.0704**
	(0.1300)	(0.0324)
Year fixed-effects	No	Yes
Fama-McBeth	Yes	No
N	22,107	22,107

Table V: CDS Strategies and Fund Tournaments

This table shows the second stage regression results of Heckman selection models. The first stage estimates the determinants of the decision to use CDS as shown in Table III. The second stage models changes in the use of each of the four principal CDS strategies. To test the tournament hypothesis we regress changes in the use of each strategy during the second half of a calendar year on excess returns during the first half of the same calendar year. Excess returns are measured as semi-annual returns over the fund-based or over the passive (corporate bond index) benchmarks. The appendix contains the descriptions of the two benchmarks used. The reported results are based on regressions that exclude the second half of 2008. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Δ(CDS notional value / TNA)$_t$							
Variables	Short multi-name CDS positions		Long multi-name CDS positions		Short single-name CDS positions		Long single-name CDS positions	
Intercept	-0.0059	-0.0156	0.0037	0.0019	0.0051	0.0099	0.0038	0.0051
	(0.0136)	(0.0148)	(0.0062)	(0.0067)	(0.0117)	(0.0126)	(0.0062)	(0.0067)
Return over fund-based benchmark$_{t-1}$	2.5959**		0.1335		-0.6072		-0.3582	
	(1.0330)		(0.4712)		(0.8867)		(0.4678)	
Return over passive benchmark$_{t-1}$		1.8666**		0.2633		-0.7807		-0.2434
		(0.8058)		(0.3650)		(0.6856)		(0.3635)
Fund flow$_t$	-0.0127	-0.0203	-0.0268	-0.0278*	-0.0171	-0.0139	-0.0202	-0.0192
	(0.0357)	(0.0359)	(0.0163)	(0.0163)	(0.0307)	(0.0307)	(0.0161)	(0.0162)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N total	280	280	280	280	280	280	280	280
N uncensored	99	99	99	99	99	99	99	99

Table VI: Short, Multi-Name CDS Strategies and Fund Tournaments

This table shows the second stage regression results of Heckman selection models. The first stage estimates the determinants of the decision to use CDS as shown in Table III. The second stage models changes in the use of the short, multi-name CDS strategy. To test the tournament hypothesis we regress changes in this strategy during the second half of a calendar year on excess returns during the first half of the same calendar year. Excess returns are measured as semi-annual returns over the fund-based or over the passive (corporate bond index) benchmarks. The appendix contains the descriptions of the two benchmarks used. We form five excess return quintiles, sorting from low (Quintile 1) to high (Quintile 5) performance, and exclude the intercept. The reported results are based on regressions that exclude the second half of 2008. The null hypothesis for the Wald test is that the coefficient of quintile 1 equals the coefficient of quintile 5. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Variables	Δ(CDS notional value / TNA)$_t$ Short multi-name CDS positions	
Return over fund-based benchmark$_{t-1}$		
Quintile 1 (lowest performance)	-0.0356***	
	(0.0117)	
Quintile 2	-0.0134	
	(0.0127)	
Quintile 3	-0.0141	
	(0.0128)	
Quintile 4	-0.0105	
	(0.0134)	
Quintile 5 (highest performance)	-0.0095	
	(0.0139)	
Return over passive benchmark$_{t-1}$		
Quintile 1 (lowest performance)		-0.0363***
		(0.0121)
Quintile 2		-0.0217*
		(0.0129)
Quintile 3		-0.0064
		(0.0124)
Quintile 4		-0.0132
		(0.0124)
Quintile 5 (highest performance)		-0.0272**
		(0.0138)
Fund flow$_t$	-0.0101	-0.0225
	(0.0363)	(0.0360)
Time fixed-effects	Yes	Yes
Wald test: Quintile 1 = Quintile 5 (p-values)	0.0697	0.5056
N total	280	280
N uncensored	99	99

Table VII: Fund Tournaments and Fund Age

This table shows the second stage regression results of Heckman selection models. The first stage estimates the determinants of the decision to use CDS as shown in Table III. The second stage models changes in the use of short-multi-name CDS. To test the tournament hypothesis we regress changes in the CDS position during the second half of a calendar year on the excess return during the first half of the same calendar year. Excess returns are measured as semi-annual returns over the mutual fund-based or the passive (corporate bond index) benchmarks. The appendix contains the descriptions of the two benchmarks used. *Young fund* is a dummy variable that equals one if a fund's age is less than the median age of 19 years and zero otherwise while *Active fund* is a dummy variable that equals one if a fund's turnover ratio is above the median. The reported results are based on regressions that exclude the second half of 2008. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Δ(CDS notional value / TNA)$_t$			
Variables	Short multi-name CDS positions			
Intercept	-0.0111	-0.0190	-0.0039	-0.0122
	(0.0145)	(0.0158)	(0.0161)	(0.0177)
Return over fund-based benchmarks$_{t-1}$	0.2917		-1.5202	
	(1.3445)		(1.4659)	
Return over fund-based benchmarks$_{t-1}$ x Young fund	4.8607**		3.2717*	
	(1.8925)		(1.8890)	
Return over fund-based benchmarks$_{t-1}$ x Active fund			4.9913***	
			(1.8557)	
Return over passive benchmarks$_{t-1}$		0.2846		-0.6806
		(1.1122)		(1.2215)
Return over passive benchmarks$_{t-1}$ x Young fund		2.6014**		1.8483
		(1.2924)		(1.2521)
Return over passive benchmarks$_{t-1}$ x Active fund				2.4240*
				(1.3398)
Young fund (dummy)	-0.0012	-0.0017	-0.0014	-0.0027
	(0.0089)	(0.0090)	(0.0091)	(0.0094)
Active fund (dummy)			-0.0074	-0.0052
			(0.0096)	(0.0100)
Fund flow$_t$	-0.0184	-0.0171	-0.0119	-0.0102
	(0.0359)	(0.0365)	(0.0353)	(0.0366)
Time fixed-effects	Yes	Yes	Yes	Yes
N total	280	280	280	280
N uncensored	99	99	99	99

Table VIII: Impact of Past Performance on Asset Composition and Trading Activity

This table shows the second stage regression results of Heckman selection models. The first stage estimates the determinants of the decision to use CDS as shown in Table III. The second stage models changes in the asset composition (Columns 1-4), the net cash ratio (Columns 5 and 6), and the asset turnover ratio (Columns 7 and 8). To test the tournament hypothesis we regress changes in the asset composition, the net cash ratio, and the asset turnover ratio during the second half of a calendar year on excess returns during the first half of the same calendar year. We measure changes in the asset composition by two types of average ratings. In Columns 1 and 2, we use the bonds' average, cumulative 5-year default frequencies, while we use the share of junk rated (below BBB-) bonds in Columns 3 and 4. Excess returns are measured as semi-annual returns over the mutual fund-based or the passive (corporate bond index) benchmarks. Appendix A1 contains the descriptions of the two benchmarks used. The reported results are based on regressions that exclude the second half of 2008. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Change in Asset Composition							
Variables	Δ (Average 5-year default frequency)$_t$		Δ (Proportion of junk-rated debt)$_t$		Δ(Net cash ratio)$_t$		Δ(Asset turnover ratio)$_t$	
Intercept	0.0005**	0.0005**	0.0254**	0.0233*	-0.0977***	-0.1036***	-0.0329	-0.0216
	(0.0002)	(0.0002)	(0.0127)	(0.0127)	(0.0343)	(0.0344)	(0.0616)	(0.0599)
Return over fund-based benchmark$_{t-1}$	-0.0103		-0.4350		3.1312		4.1560	
	(0.0200)		(1.0533)		(2.7395)		(4.9867)	
Return over passive benchmark$_{t-1}$		-0.0105		-0.8573		1.3223		8.7365**
		(0.0153)		(0.8035)		(2.0755)		(3.7809)
Fund flow$_t$	0.0004	0.0005	0.0120	0.0143	0.1963**	0.1879**	-0.4284**	-0.4628***
	(0.0007)	(0.0007)	(0.0360)	(0.0358)	(0.0917)	(0.0927)	(0.1733)	(0.1701)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N total	254	254	254	254	275	275	280	280
N uncensored	96	96	96	96	94	94	99	99

Table IX: Robustness Tests

This table shows robustness tests for short, multi-name CDS strategies. The first five columns show the second stage regression results of Heckman selection models. The first stage estimates the determinants of the decision to use CDS as shown in Table III. The regressions in Columns I and II exclude observations, for which we observe a change in the fund manager(s) between the first and second half of the same calendar year. Columns III and IV report regression results in which the dependent variable is not scaled by a fund's TNA. In Column V a value-weighted fund-based benchmark is used instead of an equally-weighted fund-based benchmark. Columns VI and VII report coefficients from seemingly unrelated regression (SUR) models in order to take potential correlation among residuals of the four different CDS strategies into account (we omit the results for the other three CDS strategies). Otherwise, we follow the baseline specification of Table V. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Δ(CDS Notional value / TNA)$_t$		Δ(CDS Notional value)$_t$		Δ(CDS Notional value / TNA)$_t$	Δ(CDS Notional value / TNA)$_t$	
Variables	I	II	III	IV	V	VI	VII
Intercept	-0.0170	-0.0336**	-0.1294	-0.2169**	-0.0001	0.0065	-0.0179
	(0.0116)	(0.0131)	(0.0980)	(0.1065)	(0.0135)	(0.0081)	(0.0109)
Return over fund-based benchmark$_{t-1}$	2.7939***		20.4758***			2.4874**	
	(0.9425)		(7.4119)			(1.0172)	
Return over passive benchmark$_{t-1}$		2.4174***		16.2416***			1.8567**
		(0.7321)		(5.7429)			(0.8049)
Return over fund-based benchmark$_{t-1}$					2.8652***		
(value-weighted)					(1.0797)		
Fund flow$_t$	-0.0585*	-0.0705**	-0.2737	-0.3399	-0.0122	-0.0115	-0.0198
	(0.0334)	(0.0335)	(0.2567)	(0.2587)	(0.0355)	(0.0356)	(0.0358)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N total	228	228	280	280	280	99	99
N uncensored	84	84	99	99	99		

Appendix: Construction of Benchmarks

We use two benchmarks to evaluate the performance of our sample of corporate bond funds. The first benchmark is calculated by the average return of all U.S. corporate bond funds of the respective Lipper fund class of Panel I. We call this benchmark the *fund-based benchmark*. The second benchmark, denoted *passive benchmark*, measures the return of a portfolio of corporate bonds that is comparable to the bond holdings of a particular fund. Panel I shows how we match Bank of America Merrill Lynch bond indices to the seven Lipper fund classes that occur in our sample. If a reasonable match cannot be found we create a new index from two or three bond indices. We use Moody's U.S. corporate rating distributions to determine the weights for the construction of the new indices. In the case of the Intermediate Investment Grade Debt Funds (Short Investment Grade Debt Funds) there is no A 3-5Y (1-3Y) index. These weights are given to AA and BBB indices accordingly. Panel II shows Moody's U.S. corporate rating distribution for the period 2004 to 2008. This data is extracted from Moody's Default Report 2008.

Panel I: Construction of passive benchmarks

Lipper fund class	Weight	Bond index
Panel A: Investment grade funds		
Corporate Debt Funds (A-Rated)	100%	US CORP A
Corporate Debt Funds (BBB-Rated)	100%	US CORP BBB
Intermediate Investment Grade Debt Funds	5%	US CORP AAA 3-5Y
	40%	US CORP AA 3-5Y
	55%	US CORP BBB 3-5Y
Short Investment Grade Debt Funds	5%	US CORP AAA 1-3Y
	40%	US CORP AA 1-3Y
	55%	US CORP BBB 1-3Y
Short-Intermediate Investment Grade Debt Funds	26%	US CORP AA-AAA 1-5Y
	74%	US CORP BBB-A 1-5Y
Panel B: High yield funds		
Multi-Sector Income Funds	100%	GLB BROAD
High Current Yield Funds	54%	US HY CORP.BB
	29%	US HY CORP.B
	17%	US HY CORP.C

Panel II: Moody's U.S. corporate rating distribution

Rating	2004	2005	2006	2007	2008	Average	Ratio
Aaa	143	144	139	150	182	152	3%
Aa	611	632	670	702	795	682	13%
A	1,204	1,242	1,279	1,298	1,240	1,253	24%
Baa	1,175	1,175	1,176	1,164	1,138	1,166	22%
Ba	555	559	598	598	590	580	11%
B	901	967	1,041	1,197	1,210	1,063	20%
Caa-C	281	330	348	334	425	344	7%
Investment grade	3,133	3,193	3,264	3,314	3,355	3,252	62%
High yield	1,737	1,856	1,987	2,129	2,225	1,987	38%
All	4,870	5,049	5,251	5,443	5,580	5,239	100%