The Use of Credit Default Swaps by U.S. Fixed-Income Mutual Funds

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March 14, 2011

Abstract

We examine the use of credit default swaps (CDS) in the U.S. mutual fund industry. We find that among the largest 100 corporate bond funds the use of CDS has increased from 20% in 2004 to 60% in 2008. Among CDS users, the average size of CDS positions (measured by their notional values) increased from 2% to almost 14% of a fund's net asset value. Some funds exceed this level by a wide margin. Funds appear both as buyers and sellers of credit protection, but on average are net sellers. Funds' net positions fluctuate significantly over time, suggesting that funds use CDS for market timing rather than hedging purposes. Consistent with the tournament hypothesis, midyear underperforming funds use CDS strategies that tend to increase a fund's exposure to credit risk during the second half of a year. These strategies further contribute to the fund's underperformance.

JEL-Classification: G11, G15, G23

Keywords: Corporate bond fund, credit default swap, credit risk, fund performance, hedging, speculation, tournaments

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We thank Carsten Hirsch, Holger Kraft, Paul Kupiec, Darius Miller, Alexandra Niessen, George Pennacchi, Stefan Ruenzi, Pablo Ruiz-Verdú, Clemens Sialm, Laura Starks, Peter Tufano, and seminar participants at CUHK, EBS Business School, Erasmus University of Rotterdam, ESMT, the 2009 FDIC fall workshop, HKU, HKUST, University of Mannheim, Nanyang Technological University, the University of Texas at Austin, and the Wirtschaftsuniversitaet Wien for very helpful suggestions and comments. We further thank Dominika Galkiewicz and Felix Miebs for excellent research assistance. Financial support by the German Science Foundation (DFG) and the Federal Deposit Insurance Corporation (FDIC) is gratefully acknowledged.

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We examine the use of credit default swaps (CDS) in the U.S. mutual fund industry. We find that among the largest 100 corporate bond funds the use of CDS has increased from 20% in 2004 to 60% in 2008. Among CDS users, the average size of CDS positions (measured by their notional values) increased from 2% to almost 14% of a fund's net asset value. Some funds exceed this level by a wide margin. Funds appear both as buyers and sellers of credit protection, but on average are net sellers. Funds' net positions fluctuate significantly over time, suggesting that funds use CDS for market timing rather than hedging purposes. Consistent with the tournament hypothesis, midyear underperforming funds use CDS strategies that tend to increase a fund's exposure to credit risk during the second half of a year. These strategies further contribute to the fund's underperformance.

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When it comes to bond funds, "there is value in the complexity." (Bill Kohli, manager of Putnam Diversified Income Trust)[1]

1 Introduction

The major end-users of credit default swaps (CDS) are banks, hedge funds and insurance companies, some of which have experienced severe losses during the past financial crisis due to their CDS positions. For example, the world's largest insurance company, AIG, was brought to the brink of collapse due to its use of CDS. Mutual funds too can be heavy end-users of CDS, exposing investors, possibly unknowingly, to significant risks. For example, the Oppenheimer Champion Income Fund, lost 74% of its net asset value in 2008, partially due to its CDS positions, and is now involved in a class-action law suit brought against it by some of its fund investors. In general, CDS can be used to hedge credit risk, to take on credit risk (and leverage) by providing credit protection to others, or to arbitrage financial markets. Little is known, however, why mutual funds use CDS, and whether the use of CDS benefits fund investors.

The objective of this paper is to examine how widespread is the use of CDS among U.S. mutual funds, what CDS strategies are being used and why, and how the use of CDS has impacted fund performance. Our data allow us to differentiate between risk-increasing and risk-decreasing CDS strategies. Thus, we can directly test the tournament hypothesis first articulated by Brown, Harlow, and Starks (1996).

We study the use of CDS since 2004, the first date since U.S. mutual funds were required to disclose information about their derivatives holdings twice a year by filing Form N-Q with the SEC. This information allows us to analyze the determinants of four major CDS strategies: long

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[1] Jeffrey R. Kosnett, May 20, 2008, With Bond Funds, Keep it Simple, Kiplinger.com.

or short single-name CDS, and long or short multi-name CDS.[2] The period 2004 to 2008 is also of particular interest as it encompasses a period of slightly declining credit risk premia, until early 2007, and subsequently strongly increasing credit risk premia (see Figure 1).

We find that among the largest 100 U.S. corporate bond funds the use of CDS has increased from about 20% of funds in 2004 to 60% of funds in 2008. The size of the average CDS position (measured by the notional value relative to a fund's net asset value) increased from 2% in 2004 to almost 14% in 2008. While for most funds CDS represent less than 10% of the fund's net asset value, some funds exceed this level by a wide margin, especially during 2008.[3]

Corporate bond funds are generally net sellers of CDS rather than net buyers. This implies that on average funds use CDS to increase their credit exposures rather than to hedge credit risk. The most frequent strategy is to sell single-name CDS, which can be used to synthetically replicate a bond investment. While during our sample period funds were always net sellers of single-name CDS, funds switch between being net sellers and net buyers of multi-name CDS. While buying credit protection can reduce a fund's overall credit risk exposure, the high volatility in the multi-name CDS positions suggests that funds may be using multi-name CDS to time the market rather than to hedge credit risk.

Consistent with the possibility that multi-name CDS are used to actively take positions in credit markets, we find that funds that use CDS generally exhibit higher asset turnovers than CDS non-users. Some authors identify higher asset turnovers with more actively managed funds. The

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[2] Single-name CDS are contracts on one reference entity, i.e., a particular bond while multi-name CDS are contracts written on a portfolio of bonds, or a CDS index.

[3] For six funds in our sample the notional values of the CDS positions exceeded 50% of the fund's NAV. These were: Intermediate Term Bond Fund (First American Investment Funds), Oppenheimer Champion Income Fund, Putnam Diversified Income Trust, Putnam Income Fund, Western Asset Core Bond Portfolio, and Western Asset Core Plus Bond Portfolio.

higher liquidity in many CDS compared to corporate bonds would make multi-name CDS the preferred instrument for active fund managers.

Since CDS can be used to increase a fund's exposure to credit risk, our data allows us to directly test the tournament hypothesis (Brown, Harlow, and Starks, 1996). According to this hypothesis, there is a convex relation between past fund performance and future fund flows. Since the compensation of most fund managers is at least implicitly tied to a fund's NAV, underperforming fund managers may have incentives to increase fund risk in order to improve their relative performance rankings and thus benefit from additional fund inflows.[4] A difficulty in testing this hypothesis is that many studies do not observe managerial actions directly, but infer the use of risk-increasing strategies indirectly from changes in a fund's return volatility. Since short CDS positions increase a fund's exposure to credit risks, ceteris paribus, we can conduct a direct test of the tournament hypothesis.

First, we verify the existence of a convex relation between past fund performance and future fund flows for a broad sample of U.S. fixed income bond funds between 1977 and 2009. Second, we show that funds that underperform during the first half of a calendar year tend to increase their short multi-name CDS positions during the second half of a calendar year. 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. We find no evidence of risk-shifting using single-name CDS positions. This is of little surprise, as single-name CDS tend to be significantly less liquid than multi-name CDS, and further expose the user to idiosyncratic risks.

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[4] Hu, Kale, Pagani, and Subramanian (2010) proposed a similar argument based on career concerns.

Finally, we test whether the changes in the size of the CDS positions we observe improve or reduce performance. First, we find that funds that use CDS perform worse on average, in terms of both raw and relative fund returns, than funds that do not use CDS. For example, the relative return differential between CDS users and CDS non-users is about 40-50 basis points p.a. between 2004 and 2008 after controlling for various style and risk characteristics. Second, we find that funds tend to increase their short multi-name CDS positions before credit risk premia fall, and decrease them before credit risk premia rise. This effect is present over the entire sample period 2004 – 2008, and not just during the financial crisis. It implies that changes in funds' CDS positions have caused losses on average, and therefore must have contributed to the underperformance of CDS users. Thus, the poor performance of CDS users is caused by at least two reasons: self-selection and poor market-timing ability.

The rest of the article is structured as follows. Section 2 reviews the related literature. Section 3 describes the data and the data sources. Section 4 contains our econometric analysis, and Section 5 concludes.

2 Literature

Our results contribute to several strands of the literature. First, to the best of our knowledge, our study is the first that examines the use of CDS by mutual funds. A few papers examine 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 were used mostly for trading rather than for hedging purposes. The authors conclude that the use of credit derivatives is limited because banks are unable to use hedge accounting when hedging with credit derivatives. In contrast, Hirtle (2009) shows that U.S. commercial banks are net buyers of credit protection, suggesting that banks may be hedging. However, he too finds that the CDS positions are small relative to banks' 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.

Several studies have examined the use of derivatives by mutual funds, but none has focused on CDS in particular or specific derivatives strategies as we do. Koski and Pontiff (1999) survey equity mutual funds and find that the use of derivatives is positively correlated with asset turnover and membership in a fund family. 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. Our results are largely consistent with these findings, except that we find no significant correlation between fund size and the use of CDS. This may be because we focus on the largest 100 corporate bond funds rather than all bond funds. In addition, we find that funds that are managed by a single manager rather than a team are more likely to use CDS. One advantage of focusing on CDS is that the available data allows us to examine why funds are using derivatives, i.e., we can distinguish between derivatives strategies that increase or decrease total fund risk. The prior mutual fund literature has only examined the use and the extent of derivatives usage.

Deli and Varma (2002) and Almazan, Brown, Carlson, and Chapman (2004) investigate the investment constraints that mutual funds impose on their fund managers. Deli and Varma

(2002) argue that more investment flexibility can reduce transaction costs, and find that funds with the highest transaction cost benefits are more likely to permit investments in derivatives. In contrast, Almazan, Brown, Carlson, and Chapman (2004) argue that providing more investment flexibility can increase agency costs. They show that constraints on derivatives are more common if the board contains a higher proportion of inside directors, if the portfolio manager is more experienced, if the fund is managed by a team rather than an individual, and if the fund does not belong to a larger fund family. Almazan, Brown, Carlson, and Chapman (2004) further show that only a small number of funds, who are permitted to do so, use derivatives.

The literature most relevant to our research is the literature on fund tournaments. Several authors, e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Elton, Gruber, and Blake (2003), find that underperforming fund managers tend to increase fund risk relative to overperforming fund managers. This is, for example, due to a convex fund flow – performance relationship, i.e., the best performing funds receive the highest inflows of new money (see Sirri and Tufano, 1998 and Gutierrez, Maxwell, and Xu, 2009), and the fact that the compensation of most fund managers is linked to the size of the fund and hence new fund inflows.[5] Koski and Pontiff (1999) also document an increase in fund risk for mid-year underperforming funds, but this effect is less strong for derivatives users. Kempf and Ruenzi (2008) find evidence of fund tournaments within fund families. Aragon and Nanda (2010) find evidence of tournament behavior also among hedge funds.[6]

[5] Sirri and Tufano (1998) further show that fund flows are more sensitive to performance differences of high return funds than of low return funds. Thus, tournament incentives should be stronger among top performing rather than poorly performing funds.
[6] Some authors have found evidence that is not consistent with tournament behavior. For example, Kim (2010) shows that the flow-performance relationship after the year 2000 is no longer convex. Busse (2001), however, argues that the evidence in favor of risk-shifting is due to the mismeasurement of the volatility estimates of monthly returns.

Incentives for risk-shifting not only arise from a convex flow-performance relationship, but can also be derived from general career concerns. For example, Hu, Kale, Pagani, and Subramanian (2010) show that both under- and overperforming managers have incentives to increase fund risk due to job loss considerations. Kempf, Ruenzi, and Thiele (2010) argue that a manager's incentive to change fund risk depends on both midyear performance and employment risk (risk of job loss). They show that in bull markets, when employment risk is low, midyear losers increase risk by more than winners, while in bear markets, when employment risk is high, midyear losers increase risk by less than winners.

We add to the tournament literature by showing that underperforming corporate bond funds increase fund risk by increasing the size of their short, multi-name CDS positions. Thus, we directly observe fund managers' actions, rather than inferring strategy changes from changes in a fund's risk characteristics.

Finally, some authors have examined the impact of derivatives usage on mutual fund performance. For example, Koski and Pontiff (1999) find that 21% of equity funds use derivatives, but there are no statistical differences in the risk and return characteristics between funds that use derivatives and those that do not. However, the impact of past performance on fund risk is significantly less for funds that use derivatives than for funds that do not. Almazan, Brown, Carlson, and Chapman (2004) also find no evidence that the permission to use derivatives correlates with equity fund returns. Johnson and Yu (2004) find that among Canadian domestic equity funds derivatives users have lower returns and higher risk than non-users. Among fixed-income funds, however, derivatives users have higher risk and higher return levels than non-users. Johnson and Yu (2004) do not explain why they observe these differences, however. Marin and Rangel (2006) provide empirical evidence for Spanish mutual funds. In their sample, 44% of fixed-income funds use derivatives. Funds that use derivatives slightly outperform non-users. In addition, these authors find evidence suggesting derivatives are used for speculation. All of these studies base their conclusions on univariate comparisons. Hence, they leave the question unanswered, whether derivatives usage impacts fund performance. In contrast, we examine how CDS position changes correlate with future credit risk premium changes, and find that fund managers adjust their CDS positions in ways that must have negatively affected fund performance.

3 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.[7] 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. 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 net asset value that 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 make 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

[7] 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.

observation period in December 2008 to avoid survivorship bias.[8] For each fund we obtain information on fund name, fund family, manager names, fund advisor name, net asset value (NAV), 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 average 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, the expiration date of the swap, the counterparty, whether the swap was bought or sold, the swap premium, and the unrealized gain or loss of the swap position.[9] 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 NAV of $73 billion. The smallest fund is the Federated Strategic Income Fund by Federated Fixed Income Securities with a NAV of $1 billion. The most common Lipper fund classes among 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

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[8] 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.

[9] 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.

Lipper fund classes we classify multi-sector income and high current yield funds as *high yield*, and all other funds as *investment grade*.[10]

For our performance analysis 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.[11] 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 Appendix A1 for further details.

4 Results

In this section we first describe the use of CDS strategies among the top U.S. corporate bond funds. Next, we examine whether the use of CDS could be motivated by fund tournament considerations. Finally, we analyze the impact of CDS usage on fund performance.

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[10] 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.
[11] In robustness tests we also use value-weighted return indexes.

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

In this section we describe the top 100 U.S. corporate bonds funds in terms of fund size and other fund characteristics. We also describe the size, type and direction of the CDS positions used by these funds, and how CDS strategies evolved over time. One objective is to determine whether fund managers use CDS to increase their fund's exposure to credit risk or to hedge credit risk of the existing bond positions.

Table 1 shows summary statistics for the top 100 bond funds. Not surprisingly, bond funds are large. The mean and median NAVs are $5 billion and $2 billion respectively. The dispersion in fund sizes is large and highly skewed. NAVs range from 264 million to over 130 billion. The reason why there appear to be a number of smaller funds under the top 100 is that some funds experienced significant value losses and redemptions during the financial crisis in 2008.[12] Note that the smallest of the top 100 funds in 2004 had a NAV of $1 billion.

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 NAVs above $15 billion, all belong to the group of investment grade funds. This fact affects the sample means, so that the mean NAV 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.[13] About 60% of funds are managed by a team of two or more fund managers. These figures are also similar for

[12] 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.

investment grade and high yield bonds. In contrast, however, there is a larger proportion of institutional investors among investment grade funds. On average, 44% of the NAV of investment grade funds is held by institutions, while institutions hold only 16% of the NAV of high yield funds.

The total expense ratios of the top 100 funds range from 0.13% to 1.75%.[14] There are nine index funds in our sample, which feature average total expense ratios of less than 0.25%. The total expense ratios of investment grade funds average about 0.61%, while the total expense ratios of high yield funds are almost double and average at 1.06%. Consistent with Moneta (2009) 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 27% of high yield funds use CDS. The next section provides an explanation of this result.

Table 2 shows how funds' NAVs and their CDS positions have evolved over time. While the mean NAV increased from $4.2 billion in 2004 to $5.7 billion in 2008, the median NAV remained roughly constant at $2 billion. This implies that only a minority of funds were able to grow their net asset values over the sample period. In contrast, 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, while 35 funds never used CDS. Among the 65 CDS-using funds, 17 funds held CDS positions throughout our sample period. The frequency of using CDS

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[13] This definition of a large fund family follows Koski and Pontiff (1999).

[14] Expense ratios, turnover ratios, and the fraction of retail investors are value-weighted averages over the outstanding fund classes.

among corporate bond funds is comparable with the use of derivatives by hedge funds, as reported by Chen (2010), who finds that 71% of a large sample of hedge funds uses derivatives.[15]

Among funds that used CDS, the total notional value of CDS positions increased from an average of $103 million per fund (2% of NAV) in 2004 to an average of $632 million per fund (14% of NAV) in 2008. The most significant increases in the size of CDS positions took place in 2007 and 2008. While most funds appear to maintain modest CDS positions, some funds carried very large CDS positions relative to their NAVs as shown by the maximum values, which range from 15% to almost 70% in 2007. In 2008, the notional values of the CDS positions of three funds even exceeded those funds' NAVs. For example, the Oppenheimer Champion Income Fund had a NAV of $2.4 billion at the end of 2007, and CDS positions with a total notional value of $1.5 billion (62% of NAV). During 2008, the fund lost 74% of its value. While the size of the derivatives position was reduced nominally, it increased to 101% of NAV.

Next, we analyze the types and direction of CDS positions taken by the top 100 bond funds. We distinguish between four general 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).[16] 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. For example, single-name CDS can be used to create a synthetic corporate bond, which may provide better returns than the actual bond investment due to the

[15] 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 posses valuable private information with respect to future credit spreads.

[16] 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.

higher liquidity in the CDS market. 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.

Multi-name strategies can be used to increase (decrease) a fund’s credit risk exposure by selling (buying) CDS on a reference asset, which mimics the fund’s general asset allocation. If the reference asset does not correspond to some of the fund’s other assets, then selling CDS could help diversify the fund. The high liquidity of multi-name CDS also makes them preferred speculative instruments to take a view on the future development of credit spreads without directly affecting bond market prices. Thus, if a fund manager wishes to time the market we would expect him to do so using multi-name rather than single-name CDS.

Table 3, Panel A provides descriptive statistics of each CDS strategy. The most frequent strategy is single-name short, used by 79% of CDS users. Single-name long and multi-name short strategies are used by about 50% of CDS users, and multi-name long strategies are used by only 35% of CDS users. Panel A further shows that on average short positions of both single- and multi-name CDS were twice as large (measured by the notional amounts of CDS scaled by a fund's NAV) as long CDS positions.[17] Thus, during our sample period mutual funds used CDS to increase rather than to hedge their credit risk exposures.

Table 3, Panel B (last column) shows that the dominance of short CDS positions existed throughout the sample period. When distinguishing between single- and multi-name CDS, we find that the average single-name net position is almost always short, while the average multi-name net position switches back and forth between being long and short. This volatility suggests that multi-name CDS may be used for position taking rather than for hedging purposes. Even the high intertemporal volatility of the single-name net position suggests active management rather than a passive hedging rationale. Interestingly, the CDS users among the top 100 funds were net short in both multi- and single-name CDS during the financial crisis, which started in the second half of 2007. This was the wrong period to be net short in credit markets, and has resulted in serious losses at some funds. We will examine the impact of CDS in Section 4.3 in more detail.

Finally, Table 3, Panel B shows that multi-name CDS positions are generally larger than single-name positions. Over the entire sample period multi-name CDS positions (both short and long) are about 4-5% of a fund's NAV, while single-name CDS positions are about 2-3% of a fund's NAV. The sizes of all four CDS strategies fluctuate significantly over time. The average multi-name long position ranges from 2-7%, while average multi-name short position ranges from 1-9%. Single-name long positions range from 1-4%, while single-name short positions range from 1-5%. Thus, multi-name strategies are somewhat more volatile than single-name strategies.

Figure 2 shows histograms of the multi- and single-name CDS net positions scaled by NAV. Note that the horizontal axis displays the lower interval limits of each observation bucket,

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

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 NAV.

To summarize, by 2008, the top 100 U.S. corporate bond funds were as likely to hold CDS positions as hedge funds were to hold derivatives. Bond funds use CDS predominantly to increase a fund’s exposure to credit risk rather than to hedge credit risk. While some single-name short CDS positions can be rationalized by synthetic bond investments, the volatility in multi-name CDS positions suggests managers may be timing credit markets.

4.2 The Determinants of CDS Strategies

In this section we first examine which funds / fund managers are more likely to use CDS, and compare the results to existing studies on derivatives usage by mutual funds. The main focus, however, lies in determining whether CDS strategies are motivated by fund tournament considerations.

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 to determine the determinants of CDS usage. We further control our regressions for the fraction of a fund’s NAV held by retail investors because institutional investors may influence a fund manager regarding CDS usage, while it is unlikely that such pressure would come from retail investors. We also include fund flows as an additional control variable because managers my hold CDS (either long or short) 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, between team-managed funds and funds that are managed by a single manager, and include dummy variables for each time period to control for common time effects.

Table 4 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 is due to economies of scale if the costs of setting a CDS trading desk can be shared across several funds. An increase in the asset turnover ratio by one standard deviation increases the likelihood to use CDS by 9-14%.[18] 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 conjecture that CDS are used to take risks rather than to passively hedge risks.

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 there are more liquid CDS available in the market on good credits than on poor credits. 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.

Interestingly, 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. In addition, institutional investors appear to have a slightly positive impact on a fund's likelihood to use CDS. These results suggest that there may be corporate governance issues associated with the use of CDS. We will return to this point in Section 4.3.

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 class action suit mentioned previously alleges that the Oppenheimer Champion Income 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 and decrease their CDS long positions. Given that multi-name CDS are not subject to idiosyncratic risks, and that they tend to be more liquid than single-name CDS, we would expect multi-name CDS to be the preferred instrument to increase fund risk.

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[18] Asset turnovers are not materially affected by funds' CDS usage because the book values of a fund's total CDS

In order to test this hypothesis we proceed in two steps. First, we estimate performance – fund flow sensitivities following Sirri and Tufano (1998) to determine whether risk-shifting incentives due to fund tournaments could also exist among corporate bond funds. We estimate the following general model using annual data of all fixed income mutual funds listed in CRSP between 1977 and 2009.

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

As control variables we include the standard deviation of monthly returns as a measure of fund risk, fund size, and the total expense ratio.

Second, we test 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 measures 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 negative, we expect a positive coefficient on past performance ($\beta_1 > 0$).

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

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positions is small compared to its NAV, as shown in Table 2, Panel B.

systematic 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, CDS positions may respond to new fund in- or outflows. 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 5 reports the estimation results of equation (1) using the Fama McBeth approach 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 funds from less well performing funds underproportionally. This convexity gives underperforming managers an incentive to increase total fund risk.

Table 6 reports the estimation results of equation (2) using a Heckman selection model. In the first stage we model the decision to use CDS as in Table 4. 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.[19] Since the first stage results are similar to the results reported in Table 4, we omit them in Table 6. In the second stage, we use past performance and fund flows as the only regressors (besides time dummies) because the regressors

[19] 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 4); and that the exclusion restrictions are uncorrelated with the error terms from the second stage (not reported).

of the first stage are relatively stable over time and do not explain changes in any of the four CDS strategies. We examine multi-name and single-name CDS strategies separately, and also distinguish between long and short positions. 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 NAV). Given that short, multi-name positions average at about 4.6% of NAV, this is an economically large increase. Thus, fund managers appear to use multi-name CDS to increase fund risk following poor performance. Consistent with this result, Chen and Pennacchi (2009) find that mutual funds tend to increase the standard deviation of tracking errors as their performance declines.

Interestingly, we find evidence of tournament behavior only among short, multi-name CDS positions, but not among any of the other three CDS strategies. This is consistent with the view that multi-name CDS are the preferred instrument to increase fund risk due to their higher liquidity compared to single-name CDS. Furthermore, if managers had no view or information about the direction of credit spreads and simply used CDS as a way to increase exposure, they would short multi-name CDS to increase a fund's implicit leverage and benefit from the higher diversification of multi-name CDS.[20]

We perform several robustness tests for short, multi-name CDS strategies, which we report in Table 7. 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.

[20] While a manger of an underperforming fund could also reduce its long (multi-name) CDS position to increase fund risk, this presumes the existence of a long CDS position. Since this is not always the case, we do not find a systematic effect. On the other hand, entering into a short position is always possible.

This restriction reduces the sample size by 61 observations, but does not affect the results in any material sense. If anything, the results are even more pronounced (see Columns I and II).

To ensure that our results are not driven by changes in NAVs 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.

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.

Finally, we estimate equation (2) using a seemingly unrelated regression (SUR) model to account for the possible simultaneity of the four different CDS strategies. Again, the results remain qualitatively unchanged.

All of our regression results further indicate that the determinants of the other three strategies do not follow tournament rationales, but follow other motives. For example, short single-name CDS strategies can be motivated by the creation of synthetic bond positions, which at some times are cheaper than buying physical bonds. Long single-name CDS strategies may be motivated by negative basis trades, i.e., the credit spread in CDS markets is lower than the credit spread in the bond market. In these cases it would not be surprising that single-name positions do not correlate with fund performance. Rather they should correlate with particular market conditions.

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. 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 the fund tournament hypothesis by Brown, Harlow, and Starks (1996), or the career concerns hypothesis by Hu, Kale, Pagani, and Subramanian (2010).

4.3 The Impact of CDS Usage on Fund Performance

In this last section we examine the impact of CDS usage on a fund's performance and risk characteristics. Depending on whether CDS are used for position-taking (speculating) or hedging objectives on average, total fund risk could either increase or decrease. If managers have no private information with respect to a firm's credit risk or overall credit risk premia, expected fund performance should not be affected. If managers have market timing ability, however, then we would expect higher returns for funds that use CDS for position-taking. For example, Kosowksi, Timmermann, Wermers, and White (2006) provide evidence that a sizable minority of managers pick stocks well enough to more than cover the additional costs of stock-picking. In addition, the authors find that these managers persistently outperform their peers.

In a first step, we characterize the top 100 bond funds in terms of their average returns and standard deviation of returns. We consider both raw and relative returns, as well as fund alphas. We estimate constant and time-varying alphas following Blake, Elton, and Gruber (1993) and Huij and Derwall (2008) using a bond market, a high-yield and a mortgage securities factor. Time-varying alphas are estimated by a smoothed Kalman filter.[21]

[21] Refer to Kim and Nelson (2000) for a general overview and Kim, Morley, and Nelson (2001) for an appearance in the finance literature.

Panel A of Table 8 shows descriptive statistics. Between 2004 and 2008 the top 100 bond funds yielded semi-annual returns of 1% on average, ranging from -24% to +8%. On average, the top 100 bond funds underperformed other corporate bond funds by 0.24% p.a., and underperformed comparable corporate bonds by 0.48% p.a. The variability in the relative performance is high, which ranges from -30% to +16% p.a. Our results are in line with Blake, Elton, and Gruber (1993) and Ferson, Henry, and Kisgen (2006) who also document underperformance for various types of fixed-income funds.

Panel B of Table 8 shows that among the top 100 funds CDS users underperform non-users by 3.7% p.a. This difference in raw returns is economically very large, and caused by a number of factors. During the second half of 2008, CDS strategies performed especially poorly. If we exclude the second half of 2008 from the analysis the difference in returns between CDS users and non-users declines to 1.2% p.a. (not reported). In terms of relative performance, CDS users also performed worse than CDS non-users, by about 0.7-0.8% p.a. The two alpha measures confirm these results. CDS users have significantly lower alphas than non-users. These differences are smaller but remain highly significant if we exclude the second half of 2008 (not reported). Interestingly, we observe no significant return differences between funds that were net short or net long in CDS.

Since the univariate analysis in Table 8 does not control for other factors that may also affect performance, we perform a multivariate analysis of funds' raw and relative returns in Table 9. Here we regress fund returns and alphas on the CDS-user dummy variable and fund characteristics, such as fund size, asset turnover, fund age, association with a larger fund family, the fraction of the fund held by retail investors, and whether a fund is an investment grade or high yield fund. We control for common time effects by including time fixed-effects.

The multivariate analysis confirms that CDS users have significantly lower returns than CDS non-users. The raw return difference is 80 bp p.a. The relative return differences are 46-58 bp p.a.[22] CDS users also appear to have lower alphas than non-users. In addition, we find that larger funds and investment grade funds have higher raw and relative returns as well as higher alphas.

Next, we examine the standard deviations of returns of CDS users and non-users. The univariate analysis in Table 8, Panel B shows that CDS users have higher standard deviations of both raw and relative returns than CDS users. These differences seem to be driven by those funds that were net short in CDS, while the funds that were net long display return volatilities that were similar to the return volatilities of CDS non-users. This finding is consistent with the view that short CDS positions are used to increase a fund's total risk exposure.

In Table 10 we check whether these results hold up in a multivariate analysis. We regress the standard deviation of both raw and relative returns on the CDS user dummy variable and several control variables that may be correlated with fund risk. In all regressions we find that CDS users display higher standard deviations of returns than CDS non-users. However, the coefficient is statistically significant in the last regression only. Older funds and investment grade funds have lower volatilities than younger and high-yield funds. Surprisingly, funds with higher asset turnovers have lower return volatilities than funds with lower asset turnovers, but the economic magnitude of the coefficient is small.

Overall, we find that CDS users have significantly lower returns than non-users on average, while having the same or slightly higher standard deviations of returns than CDS non-

[22] Returns are calculated net of fund fees. Our results are robust to using gross fund returns (not reported).

users. These differences persist even after controlling for time effects.[23] The underperformance is somewhat less severe if fund alphas are considered.

The underperformance of CDS users can have several explanations. Funds that underperform may be more likely to use CDS hoping to improve performance. Our evidence presented in Table 6 supports this possibility. Alternatively funds' CDS strategies may generate losses that negatively impact performance. In order to judge whether the use of CDS has been beneficial to fund investors, we now focus on the second possibility. A challenge is the relatively short sample period (due to data availability), and the possibility that the poor performance of short CDS positions during the financial crisis is due to bad luck. We therefore focus on a partial aspect of the impact of CDS strategies on fund performance.

In Table 3 we observed that the average net multi-name CDS position fluctuated significantly between net short and net long over time. We now evaluate whether changes in the size of funds' CDS positions led to a subsequent improvement or deterioration of fund performance. For example, if a fund increased its short CDS positions before credit risk premia rose, then this would undoubtedly reduce fund performance.

To examine this possibility we follow the approach by Brown, Crabb, and Haushalter (2006) and regress changes in the sizes of each of the four CDS strategies on future credit spread changes.

$$\Delta \frac{CDS\ notional\ value_{it}}{NAV_{it}} = \alpha_i + \beta \Delta Credit\ spread_{t+1} + e_{it} \qquad (3)$$

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[23] Our main findings in Table 8 and 10 remain qualitatively unchanged if we replace the investment grade dummy with the bonds' average credit rating. We stick to our presented specification because the investment grade dummy has a higher explanatory power.

We measure the credit spread by the yield difference between Baa-rated corporate bonds and 10-year U.S. Treasury securities. We estimate changes on changes regressions to control for unobservable, time-invariant fund characteristics. The results, reported in Table 11, show that on average funds increase their short multi-name CDS positions before credit spreads rise. The effect prevails even if we exclude the whole of 2008 (not reported). Such strategy clearly yields losses, and at least partially explains why CDS users generally underperform non-users. This result is consistent with Huang, Sialm, and Zhang (2010), who find that equity funds that increase risk perform worse than funds that keep stable risk levels over time. Boney, Comer, and Kelly (2009) also find poor market timing ability among a sample of 84 investment grade bond funds.[24]

Interestingly, we find no significant correlations between the other three CDS strategies and future credit spread changes. This is consistent with our earlier conclusion that these strategies follow other determinants, and firms primarily use short multi-name CDS to time credit markets. Overall, mutual funds do not seem to be successful at this on average.

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[24] To check the robustness of our results we re-estimate all regressions in Table 11 using random-effects instead of fixed-effects (Columns 2 and 4 of Table 11), excluding the whole of 2008, and using the Aaa spread instead of the Baa spread. The results are not materially affected by these adjustments.

5 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. Thus, by now the frequency of CDS usage among the largest bond mutual funds is comparable to the frequency of derivatives usage by hedge funds. The size of CDS positions (measured by the notional value) is usually less than 10% of a fund's net asset value, 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. While funds are generally net sellers of single-name CDS, they switch between being net sellers and net buyers of multi-name CDS. This volatility suggests that some fund managers use multi-name CDS to time credit markets rather than to hedge credit risk. Consistent with this possibility, we find that funds increase their short (multi-name) CDS positions when credit risk premia rise. Such strategy may stem from a belief in mean-reversion of credit spreads.

In fact, it is the underperforming funds that tend to increase fund risk by increasing their short, multi-name CDS positions. This result is consistent with the tournament hypothesis advanced by Brown, Harlow, and Starks (1996), which states that underperforming funds increase fund risk to try to improve their relative performance. Multi-name CDS would be the instrument of choice due to their higher liquidity compared to many corporate bonds. Finally, we examine the performance of funds' CDS strategies. Generally, funds that use CDS exhibit lower returns and the same or slightly higher standard deviations than funds that do not use CDS. This result holds before and during the financial crisis. Part of the reason for this underperformance is that on average funds increase their short (multi-name) CDS positions before credit spreads rise and decrease their short (multi-name) CDS positions before credit spreads fall. This unfortunate "market timing" must have contributed to the general underperformance of CDS users.

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Figure 1: Credit Spreads

This figure shows the evolution of credit spreads defined by the difference between the average yield on Aaa-rated (Baa-rated) corporate debt (Moody's yield on seasoned corporate bonds) and the yield on 10-year U.S. Treasury securities between July 2004 and December 2008.

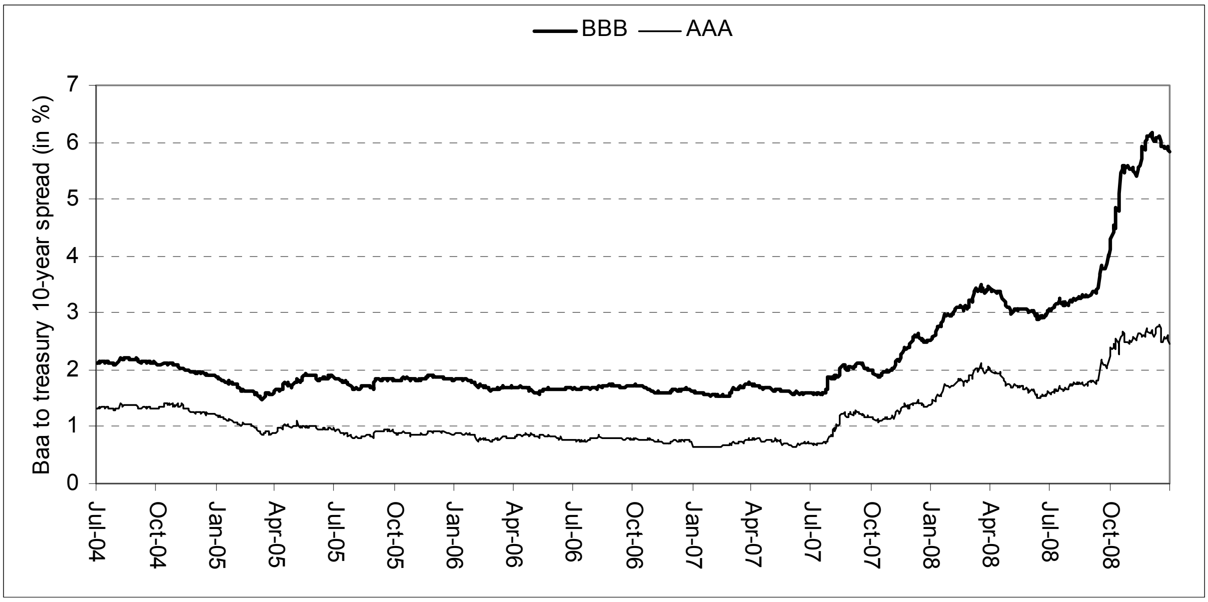
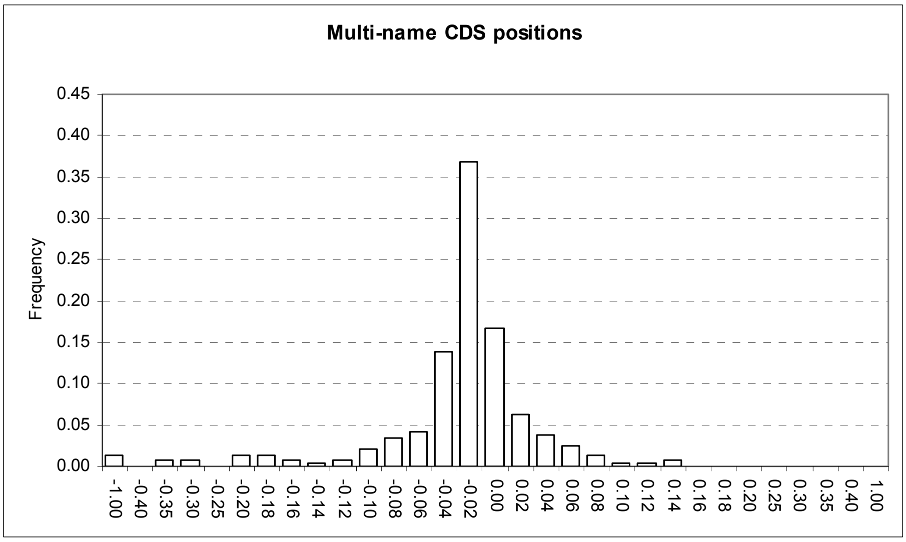


Figure 2: The Distribution of Net Notional Amounts of CDS Positions

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 net asset values (NAV). The sample is comprised of the largest (by NAV) 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 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.



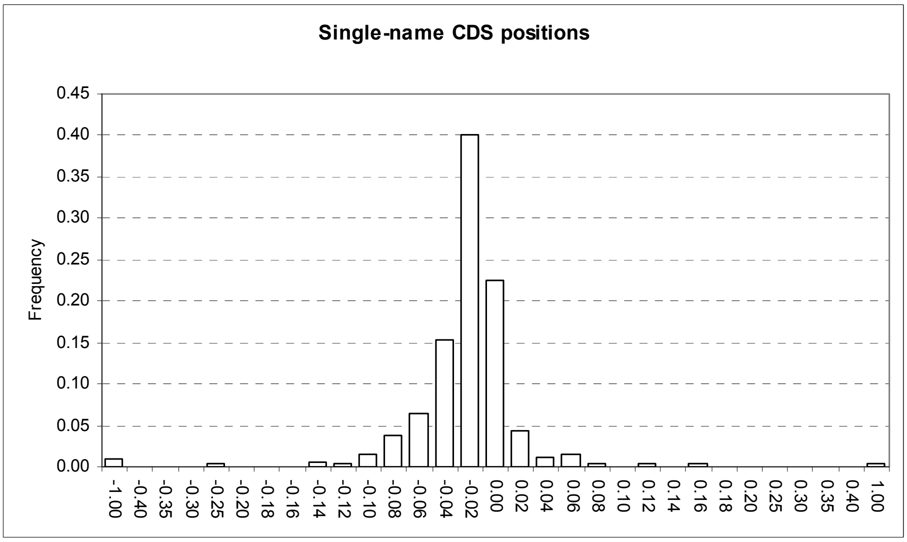


Table 1: Fund Characteristics

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 net asset value, NAV) 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 retail investors* is the proportion of a fund's total NAV held by retail investors (net asset value of retail investor fund classes / total NAV). The *asset turnover ratio* is defined as the minimum of aggregated sales and purchases of securities divided by the 12-month average NAV. *Total expense ratio* is the sum of a fund's operating expenses (including 12b-1 fees, waivers and reimbursements) over a fund's total NAV. *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 $(NAV_t - NAV_{t-1}(1 + \text{semi-annual return}_t))/NAV_{t-1}$. *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.

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Panel A: All funds								
Total NAV (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 retail investors	890	0.66	0.40	0.00	0.19	0.91	1.00	1.00
Asset turnover ratio (p.a.)	890	1.36	1.42	0.00	0.48	0.81	1.74	10.81
Total expense ratio (% p.a.)	890	0.78	0.35	0.13	0.55	0.75	1.07	1.75
Team managed (dummy)	890	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Fund flow (semi-annual)	890	-0.011	0.116	-0.355	-0.084	-0.023	0.051	0.367
CDS usage (dummy)	890	0.41	0.49	0.00	0.00	0.00	1.00	1.00
Panel B: Investment grade funds								
Total NAV (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 retail investors	544	0.56	0.43	0.00	0.07	0.64	1.00	1.00
Asset turnover ratio (p.a.)	544	1.79	1.65	0.00	0.59	1.32	2.52	10.81
Total expense ratio (% p.a.)	544	0.61	0.27	0.13	0.48	0.60	0.73	1.42
Team managed (dummy)	544	0.58	0.49	0.00	0.00	1.00	1.00	1.00
Fund flow (semi-annual)	544	0.010	0.123	-0.355	-0.060	0.002	0.072	0.367
CDS usage (dummy)	544	0.50	0.50	0.00	0.00	0.00	1.00	1.00
Panel C: High yield funds								
Total NAV (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 retail investors	346	0.84	0.28	0.00	0.85	0.96	1.00	1.00
Asset turnover ratio (p.a.)	346	0.67	0.36	0.00	0.41	0.58	0.83	2.02
Total expense ratio (% p.a.)	346	1.06	0.27	0.18	0.86	1.10	1.22	1.75
Team managed (dummy)	346	0.62	0.49	0.00	0.00	1.00	1.00	1.00
Fund flow (semi-annual)	346	-0.043	0.098	-0.355	-0.106	-0.055	-0.001	0.367
CDS usage (dummy)	346	0.27	0.45	0.00	0.00	0.00	1.00	1.00

Table 2: Fund Size and CDS Usage

The table shows funds' net asset values (NAV) in $ million (columns 1 and 2), the number of CDS users out of the top 100 U.S. corporate bond funds (column 3), and the mean notional amount of a fund's total CDS positions at a particular point of time (column 4). Columns 5 to 7 show the total notional value of CDS positions over the NAV per fund.

	NAV			Mean CDS	CDS notional amount / NAV		
Period	Mean	Median	CDS users	notional amount	Mean	Min	Max
2004 02	4,247	2,041	21	103	0.0205	0.0012	0.1523
2005 01	4,379	2,001	30	216	0.0411	0.0014	0.2662
2005 02	4,520	1,996	26	315	0.0569	0.0045	0.2910
2006 01	4,579	2,074	33	296	0.0516	0.0016	0.2367
2006 02	4,959	2,158	35	387	0.0596	0.0001	0.2433
2007 01	5,347	2,289	48	444	0.0640	0.0011	0.4196
2007 02	5,692	2,359	54	527	0.0926	0.0013	0.6886
2008 01	6,026	2,285	58	787	0.1238	0.0029	1.1376
2008 02	5,659	2,038	60	632	0.1372	0.0012	1.1556

Table 3: The CDS Strategies

Panel A reports descriptive statistics of the sum of CDS notional amounts relative to a fund's NAV for four separate CDS strategies. We distinguish between CDS written on a single asset (single-name) and a portfolio of assets or an index (multi-name), and whether a position is short (protection sold) and long (protection bought). Panel B shows the notional amounts of CDS positions relative to a fund's NAV for each of the four primary CDS strategies separately (CDS users only). Columns 5 and 6 also report the net notional amounts over NAV. 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 NAV for multi- and single-name CDS lumped together.

Panel A: Descriptive statistics of CDS strategies (Notional amount / NAV)

Strategy	N	N non-zero	Mean	Min	Median	Max
Multi-name (short)	365	191	-0.029	-0.616	-0.001	0.000
Multi-name (long)	365	126	0.016	0.000	0.000	0.551
Single-name (short)	365	289	-0.025	-0.691	-0.009	0.000
Single-name (long)	365	200	0.013	0.000	0.002	1.142

Panel B: CDS strategies over time

	CDS notional amount / NAV				CDS net notional amount / NAV		CDS net notional amount / NAV
	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 4: 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 1. 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(total net asset value)	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 retail 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 5: 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 fixed income mutual funds from the CRPS survivorship-free mutual fund database covering 1977 to 2009. We also use the year 1976 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 75% in bonds and cash. We drop funds with "Equity" 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 average net asset value during year *t* (In(*NAV*)), and the sum of a fund's operating expenses (including 12b-1 fees, waivers and reimbursements) over a fund's total NAV (*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 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	0.7218***	0.3369***
	(0.0793)	(0.0601)
Raw return$_t$	1.2171**	0.5203*
	(0.5772)	(0.2589)
Raw return squared$_t$	3.8578*	0.4908*
	(2.2443)	(0.2776)
Risk$_t$	-2.4097***	-0.6244
	(0.7555)	(0.3838)
ln(NAV$_t$)	-0.0804***	-0.0742***
	(0.007)	(0.0085)
Total expense ratio$_t$	-0.0874***	-0.0983***
	(0.0297)	(0.0348)
Year fixed-effects	No	Yes
Fama McBeth	Yes	No
N	38,150	38,150

Table 6: 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 4. The second stage models changes in the use of each of the four principal CDS strategies. In the first four columns we consider multi-name CDS positions only, while in the last four columns we consider single-name CDS positions only. 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 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.

	Δ(CDS notional value / NAV)$_t$							
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	359	359	359	359	359	359	359	359
N uncensored	99	99	99	99	99	99	99	99

Table 7: Multi-Name CDS Strategies and Fund Tournaments – 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 4. 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 the NAV. 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 to account for the simultaneity of the four different CDS strategies (we omit the results for the other three CDS strategies). Otherwise, we follow the baseline specification of Table 6. Standard errors are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Δ(Notional value / NAV)$_t$		Δ(Notional value)$_t$		Δ(Notional value / NAV)$_t$	Δ(Notional value / NAV)$_t$	
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	298	298	359	359	359	99	99
N uncensored	84	84	99	99	99		

Table 8: Average Fund Returns and the Standard Deviation of Returns

This table reports fund returns and standard deviation of fund returns of the top 100 U.S. mutual corporate bonds funds between 2004 and 2008. We consider funds' raw returns, as well as fund returns relative to two benchmarks. See Appendix A1 for details. We also calculate constant and time-varying three-factor alphas. The latter are estimated using a smoothed Kalman filter. The three factors include a bond market factor, a high yield factor, and a mortgage securities factor following Huij and Derwall (2008). We use t-tests for the significance of the mean in column 2 and Wilcoxon signed-rank tests for the median in column 5. Panel B shows return differences between funds that use CDS and funds that do not, and between funds that were net short in CDS and funds that were net long. We use univariate OLS regressions in Panels I and II with standard errors that are clustered at the fund level to test whether the differences are significant. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Panel A: Descriptive statistics

	N	Mean	Std. dev.	Min	Median	Max
Panel I: Average semi-annual returns						
Raw returns	890	0.0101***	0.0498	-0.2375	0.0157***	0.0813
Returns over fund-based benchmarks	890	-0.0012**	0.0167	-0.1432	0.0011***	0.0607
Returns over passive benchmarks	890	-0.0024***	0.018	-0.1498	-0.0006***	0.0837
Three-factor alpha (constant)	890	0.0021***	0.0014	-0.0074	0.0022***	0.0050
Three-factor alpha (time-varying)	890	-0.0008***	0.0034	-0.0467	-0.0002***	0.0121
Panel II: Average semi-annual standard deviation of monthly returns						
Raw returns	890	0.0220***	0.0196	0.0066	0.0159***	0.1784
Returns over fund-based benchmarks	890	0.0123***	0.0143	0.0019	0.0079***	0.1514
Returns over passive benchmarks	890	0.0170***	0.0171	0.0052	0.0112***	0.1578

Panel B: Two-sample comparisons

	CDS			CDS users		
Period	Non-users	Users	Difference	Net short	Net long	Difference
Panel I: Average semi-annual returns						
Raw returns	0.0177	-0.0009	-0.0186***	-0.0016	0.0007	0.0022
Returns over fund-based benchmarks	0.0003	-0.0032	-0.0035***	-0.0037	-0.0021	0.0016
Returns over passive benchmarks	-0.0006	-0.0049	-0.0043***	-0.0058	-0.0029	0.0029
Three-factor alpha (constant)	0.0022	0.0018	-0.0004**	0.0018	0.0019	0.0001
Three-factor alpha (time-varying)	-0.0004	-0.0014	-0.001***	-0.0016	-0.0012	0.0004
Panel II: Average semi-annual standard deviation of monthly returns						
Raw returns	0.0192	0.0261	0.0069***	0.0268	0.0246	-0.0022
Returns over fund-based benchmarks	0.0106	0.0148	0.0042***	0.0157	0.0127	-0.0030*
Returns over passive benchmarks	0.0144	0.0207	0.0063***	0.0219	0.0181	-0.0037*

Table 9: Fund Returns – Multivariate Regression Results

This table shows OLS regression results of the semi-annual fund returns and three factor alphas of the top 100 U.S. corporate bond funds. In Column 1, the dependent variable is a fund's raw returns. In Columns 2 and 3, the dependent variables are a funds' return relative to a benchmark. See Appendix A1 for details. In Columns 4 and 5, the dependent variables are a fund's constant and time-varying three-factor alphas. See Table 6 for details. *Investment grade* is a dummy variable that equals 1 for investment grade funds and 0 for high yield funds. Definitions of the other control variables are given in Table 1. Standard errors are reported in parentheses and are clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

		Returns over benchmark		Three-factor alpha	
Variable	Raw returns	Fund-based	Passive	Constant	Time-varying
Intercept	-0.1304***	-0.0417***	-0.0389***	0.0034***	-0.0033**
	(0.0090)	(0.0071)	(0.0079)	(0.0010)	(0.0015)
CDS	-0.0040***	-0.0023**	-0.0029**	-0.0005**	-0.0001
	(0.0014)	(0.0010)	(0.0012)	(0.0002)	(0.0004)
ln(total net asset value)	0.0034***	0.0021***	0.0021***	0.0001	0.0001
	(0.0008)	(0.0006)	(0.0007)	(0.0001)	(0.0002)
Asset turnover ratio	-0.0000	-0.0002	-0.0002	-0.0000	-0.0001
	(0.0004)	(0.0003)	(0.0003)	(0.0000)	(0.0001)
ln(fund age)	-0.0010	-0.0008	-0.0006	-0.0005**	-0.0002
	(0.0011)	(0.0009)	(0.0010)	(0.0002)	(0.0002)
Big fund family (dummy)	0.0016	0.0010	0.0013	-0.0004*	-0.0004
	(0.0012)	(0.0009)	(0.0010)	(0.0002)	(0.0003)
Investment grade (dummy)	0.0051***	0.0042***	0.0060***	0.0006**	0.0002
	(0.0013)	(0.0011)	(0.0013)	(0.0003)	(0.0004)
Fraction of retail investors	0.0019	0.0011	0.0013	0.0004	-0.0001
	(0.0017)	(0.0013)	(0.0014)	(0.0003)	(0.0003)
Team managed (dummy)	-0.0018	-0.0017	-0.0016	-0.0007***	-0.0006*
	(0.0015)	(0.0011)	(0.0013)	(0.0002)	(0.0003)
Fund flows	-0.0172**	-0.0078	-0.0043	0.0021***	0.0063***
	(0.0084)	(0.0060)	(0.0069)	(0.0007)	(0.0019)
Time fixed-effects	Yes	Yes	Yes	Yes	Yes
Adj. R square	0.8410	0.3083	0.2220	0.1983	0.2661
N	890	890	890	890	890

Table 10: Standard Deviation of Returns - Multivariate Regression Results

This table shows OLS regression results of the standard deviations of monthly fund returns of the top 100 U.S. corporate bond funds. In Column 1, the dependent variable is the standard deviation of a fund's raw returns. In Columns 2 and 3, the dependent variables are the standard deviations of a fund's excess returns. See Appendix A1 for further details. *Investment grade* is a dummy variable that equals 1 for investment grade funds and 0 for high yield funds. Definitions of the other control variables are given in Table 1. Standard errors are reported in parentheses and are clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Variable	Standard deviation of fund raw returns	Standard deviation of fund returns over fund-based benchmark returns	Standard deviation of fund returns over passive benchmark returns
Intercept	0.0745***	0.0481***	0.0683***
	(0.0053)	(0.0050)	(0.0047)
CDS	0.0007	0.0007	0.0020**
	(0.0008)	(0.0008)	(0.0008)
ln(total net asset value)	0.0001	-0.0001	-0.0006
	(0.0004)	(0.0004)	(0.0005)
Asset turnover ratio	-0.0005*	-0.0006**	-0.0007**
	(0.0003)	(0.0003)	(0.0003)
ln(fund age)	-0.0012*	-0.0008	-0.0011
	(0.0006)	(0.0007)	(0.0008)
Big fund family (dummy)	0.0010	0.0005	0.0005
	(0.0007)	(0.0007)	(0.0009)
Investment grade (dummy)	-0.0020*	-0.0012	-0.0027***
	(0.0010)	(0.0010)	(0.0010)
Fraction of retail investors	-0.0010	-0.0005	-0.0013
	(0.0012)	(0.0012)	(0.0012)
Team managed (dummy)	-0.0008	0.0002	-0.0011
	(0.0007)	(0.0007)	(0.0007)
Fund flow	0.0065	0.0058	0.0064
	(0.0050)	(0.0049)	(0.0045)
Time fixed-effects	Yes	Yes	Yes
Adj. R square	0.8014	0.6409	0.7499
N	890	890	890

Table 11: Did CDS Position Changes Affect Fund Performance?

This table shows regression results of changes in each of the four principal CDS strategies. To test whether changes in a fund's CDS positions has subsequently led to improved or reduced fund performance we regress changes in a fund's CDS positions on future credit spread changes. The credit spread is measured by the Baa-rated bond yield (Aaa-rated in robustness tests) over 10-year Treasury yields in % p.a. Standard errors are reported in parentheses and are clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Δ(CDS notional value / NAV)$_t$							
Variables	Short multi-name CDS positions		Long multi-name CDS positions		Short single-name CDS positions		Long single-name CDS positions	
Intercept	0.0026	-0.0005	0.0016	0.0028**	-0.0031*	-0.0025**	0.0093**	0.0087
	(0.0045)	(0.0016)	(0.0024)	(0.0014)	(0.0017)	(0.0011)	(0.0044)	(0.0076)
Δ(Credit spread)$_{t,t+1}$	-2.0768***	-1.5482***	0.3002	0.1032	-0.3090	-0.4139	-0.7398	-0.3505
	(0.7688)	(0.4816)	(0.4041)	(0.2264)	(0.2836)	(0.3193)	(0.7571)	(0.3686)
Fund fixed-effects	Yes	No	Yes	No	Yes	No	Yes	No
Fund random-effects	No	Yes	No	Yes	No	Yes	No	Yes
R square (overall)	0.0301	0.0301	0.0004	0.0004	0.0044	0.0044	0.0000	0.0000
N	284	284	284	284	284	284	284	284

Appendix A1: 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 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%