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Pitfalls and Perils of Financial Innovation: The Use of CDS by Corporate Bond Funds

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Abstract

We use the financial crisis of 2007–2009 as a laboratory to examine the costs and benefits of teams versus single managers in asset management. We find that when a fund uses complex trading strategies involving the use of CDS team-managed funds outperform solo-managed funds. This may be due to the greater diversity of expertise, experience and skill of teams relative to single managers. During the financial crisis, however, the performance premium of teams becomes negative, which may be because of the slower decision times of teams, which are especially costly during times of rapidly changing market conditions.

JEL Classification: G11, G15, G23
Key Words: Mutual funds, management teams, financial crisis, credit default swaps, performance, market timing

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

Many corporate bonds funds have been using credit default swaps, and thus significantly increased the complexity of their potential trading strategies.[1] For example, CDS allow a fund to speculate on rising and falling credit risk premia, on counterparty risk, and to implement various arbitrage strategies. CDS also allow a manager to increase the implicit leverage of the fund. The main question we address in this paper is whether this complexity benefits the shareholders of a fund, and which management structures are better suited to unleash the alleged value for shareholders.

There is a sizable literature investigating whether team-managed or solo-managed funds perform better. Teams offer several benefits vis-à-vis solo-managed funds. Teams have a greater diversity of expertise, experience and skill relative to a single manager, which should be especially valuable if a fund is using a diversity of complex trading strategies.[2] On the other hand, teams take more time when making decisions (see Vroom, 2003). Whether the costs or the benefits of teams dominate is still an open question. Some studies find that team-managed funds perform better than solo-managed funds (see Adams, Nishikawa, Rao, 2013, and Patel and Sarkissian, 2014), while others find the opposite (see Chen, Hong, Huang, Kubik, 2004). Some studies find no significant performance differences between team-managed and solo-managed funds (see Prather and Middleton, 2002, and Bliss, Potter, and Schwarz, 2008).

The occurrence of the 2007–2009 financial crisis presents us with an opportunity to separate some of the costs and benefits of teams versus single managers. The greater diversity of expertise, experience and skill of teams should be especially beneficial if a fund is using complex investment strategies, such as those involving CDS. Thus, among funds using CDS

[1] Our data shows that about 65% of the largest 100 corporate bond funds registered in the U.S. have been using CDS since 2004.
[2] Other benefits of teams are a reduction in serious decision errors (Sharpe, 1981) and more efficient risk allocations (see Barry and Starks, 1984).

team-managed funds should outperform solo-managed funds. In contrast, the longer decision times of teams should be especially costly during rapidly changing, adverse market conditions, such as the 2007–2009 financial crisis, especially if complex trading strategies are used. Therefore, we expect the performance of teams to be lower during the 2007–2009 financial crisis than outside the crisis period vis-à-vis single manager funds.

We investigate these hypotheses at the sample of the largest 100 U.S. corporate bond funds as of 2004, which make up about 76% of the total market capitalization of all corporate bond funds registered in the U.S.[3] We follow these 100 bond funds until the end of 2010, so that the 2007–2009 financial crisis is completely contained within our sample period. We follow Ben-David, Franzoni, and Moussawi (2012) and define the financial crisis period as lasting from July 2007 until March 2009. This time was characterized by dramatic increases in the level and volatility of credit spreads and declines in market liquidity, especially as a result of the Lehman Brothers default.

We find that corporate bonds funds significantly underperformed by 52-215 basis points per month during the crisis period, which is not surprising given the strong rise in credit spreads. Interestingly, there are no significant risk and performance differences between CDS users and CDS non-users in general. A reason for this is that CDS are used for a variety of strategies, some of which yield profits during periods of rising risk premia while others yield losses.[4]

With respect to a fund's management structure, we find that during normal market conditions funds using CDS and managed by a team outperform funds using CDS but managed by a single manager. This is consistent with teams having a greater diversity of expertise, experience and skill relative to single managers, which is especially valuable if

[3] We focus on corporate bond funds because the use of CDS is concentrated in this segment of the mutual fund industry. We focus on large funds because due to the minimum contract sizes of CDS they are not suitable for smaller funds (see Meng and ap Gwilym, 2007). The high degree of skewness in fund sizes and the focus on the largest funds implies that our results are most relevant to the average investor rather than the average fund.
[4] In unreported analysis, we find that funds that were net short CDS during the crisis performed worse than funds that were net long.

using complex trading strategies. During the crisis period, however, the performance relation reverses. Funds using CDS and managed by a team underperform funds using CDS but managed by a single manager by 31-70 basis points per month. This result may be a reflection of the longer decision times of teams relative to single managers, which are especially costly during times of high uncertainty and rapid market changes. Thus, if funds make use of complex trading strategies, there is value in having a team, but this is counterbalanced by the less efficient decision-making processes of teams, which dominates during adverse market conditions.

Next, we investigate the possible reasons of this underperformance during the crisis period. We find that teams exhibited especially poor market-timing skills during the crisis. In contrast to single managers, team-managed funds increased their short CDS positions before credit spreads rose and vice versa. Team-managed funds were also more likely to be net short in their overall CDS positions than solo-managed funds during the crisis. Finally, team-managed funds increased their short positions in asset-backed securities during the crisis. Given the prevailing market conditions, all three strategies should have resulted in losses during the crisis period.

We also analyze the CDS usage of funds more generally, and find that the use of CDS by corporate bond fund managers has increased significantly over our sample period, mimicking the general development of the CDS market. While in 2004, only 21% of the largest corporate bond funds were using CDS, this fraction increased to 64% in 2008 and has stabilized at slightly below 50% since then. While the average total notional value of all CDS positions represents about 7.3% of a fund's total net assets (TNAs), some funds hold very large CDS positions, which exceed the fund's TNA.

Most funds hold both long and short CDS positions, but short positions tend to exceed long positions, so that corporate bond funds as a group were always net short in CDS over our sample period. This implies that on average funds do not use CDS to hedge credit risk, which would require long CDS positions.

Not all funds use CDS.[5] We find that funds belonging to a fund family are about 24% more likely to use CDS than funds not belonging to a fund family, which suggests that economies of scale are an important determinant of CDS usage. Investment grade funds are 24% more likely to use CDS than high-yield funds. The share of institutional investors among a fund's shareholders is also positively correlated with the likelihood of using CDS.

Our results add to several strands of the literature. Our main contribution adds to our understanding of the benefit of teams versus single managers in asset management. The literature investigating the performance of team-managed funds versus solo-managed funds has produced inconsistent evidence so far. Adams, Nishikawa and Rao (2013) and Patel and Sarkissian (2014) find that team-managed funds perform better than solo-managed funds, while Chen, Hong, Huang, and Kubik (2004) finds the opposite. Prather and Middleton (2002) and Bliss, Potter, and Schwarz (2008) find no significant performance differences between team-managed and solo-managed funds. Our results show that teams can have advantages but also costs. In normal market conditions, the greater diversity of expertise, experience and skill of teams adds value if the fund is making use of complex trading strategies. In adverse market conditions, however, the lower efficiency of decision-making of teams is costly. Chen, Hong, Huang, and Kubik (2004), Cici (2012), and Pool, Stoffman, and Yonker (2012) show that teams have a tendency to make inefficient investment decisions. Our results indicate that these inefficiencies primarily arise during adverse market conditions.

By showing that CDS have become an important tool for corporate bond funds, and that CDS are not used for hedging purposes on average, we also extend the literature on the use of derivatives by mutual funds. Koski and Pontiff (1999) survey equity mutual funds and find that the use of derivatives is positively correlated with asset turnover and membership of

[5] About 30% of funds never used CDS during our sample period.

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. Cici and Palacios (2013) find that funds that use equity options underperform funds that do not. However, the empirical evidence how derivatives usage impacts fund performance is mixed (see Koski and Pontiff, 1999; Johnson and Yu, 2004; Marin and Rangel, 2006; and Cici and Palacios, 2013). Finally, Cao, Ghysels, and Hatheway (2011) find evidence that fund managers time their use of derivatives in response to past returns.[6]

Our results also contribute to the literature on the use of CDS in general. 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, use CDS (as end-users). The exceptions are Hirtle (2009) and Minton, Stulz, and Williamson (2009), who analyze the CDS positions held by U.S. banks, and Van Ofwegen, Verschoor, and Zwinkels (2010), who analyze the CDS usage by European financial institutions. To the best of our knowledge, no study has yet been undertaken on the use of CDS by hedge funds, insurance companies, or other asset managers.

1. Sample and Construction of Variables

Since 2004, U.S. mutual funds have been required to disclose their derivatives holdings quarterly on Forms N-CSR, N-CSRS, and N-Q. Searching these forms of all mutual funds contained in the CRSP survivorship-free mutual fund database for key words such as *credit default*, *default swap*, *CDS*, *default contract*, and *default protection* yielded hits

[6] Recently, the SEC also has become interested in the use of CDS by mutual funds. See the SEC concept paper titled “Use of Derivatives by Investment Companies under the Investment Company Act of 1940” (Release No. IC-29776).

predominantly among corporate bond funds. We therefore focus our analysis on U.S. corporate bond funds, which we identify by membership of 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.

The typical contract size of a CDS is $5 million, and thus too large to be used by small funds (Meng and ap Gwilym, 2007). We therefore focus our analysis on the largest 100 U.S. corporate bond funds by TNA, which are included in the CRSP survivorship-free mutual fund database as of the end of the second quarter of 2004. This is also the most relevant set of corporate bond funds for investors and regulators because it makes up 76% of the overall market capitalization of all U.S. corporate bond funds by the end of the second quarter of 2004. We follow these 100 funds until the end of the observation period in December 2010 to avoid survivorship bias.[7]

For each fund, we obtain information on the fund name, fund family, manager names, TNAs, turnover ratio, fund classes, shares held by retail and institutional investors, fund fees, inception dates, daily and monthly fund returns from the CRSP mutual fund database. We add information on the distribution of credit ratings, the Morningstar rating, and fund manager information, such as gender, from Morningstar Direct for each fund. For the calculation of performance measures we use benchmark indices from Barclays, which are taken from Datastream.[8]

From the N-CSR and N-Q forms, we manually collect for each fund and each CDS position the notional value and whether the swap was bought or sold. This step generates

[7] We analyze disappearing funds because they 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. Five funds were discontinued and merged with other existing funds: Fidelity's Spartan Investment Grade Bond Fund was merged with the Investment Grade Bond Fund on July 28, 2006, the Oppenheimer High Yield Fund was merged with the Oppenheimer Champion Income Fund on October 12, 2006, the Evergreen Core Bond Fund and Evergreen Short Intermediate Bond Fund were both acquired by Wells Fargo Advantage Total Return Bond Fund in July 2010, and the Oppenheimer Global Strategic Income Fund became a "Global Income Fund" by the beginning of 2010.

[8] Note that Barclays continued to provide the Lehman Brothers series of fixed-income benchmark indices.

information on 44,777 CDS positions. From the SEC's Form N-SAR, which registered investment companies must file twice a year (Deli and Varma, 2002; Almazan, Brown, Carlson, and Chapman, 2004), we also collect information on whether funds were engaged in repos, debt options, interest futures, and borrowing. Since those four strategies are highly correlated with each other, we construct a numerical score (*Form N-SAR score*), which equals the sum of the strategies in which a fund is simultaneously engaged. This score thus takes on values between 0 and 4, and controls for other complex trading strategies beyond the complexity achieved by CDS strategies.

2. Risk and Performance Measures

We characterize funds in terms of their risks and returns using the following risk and performance measures. All measures are calculated, if appropriate, on a monthly frequency. In particular, we estimate the respective measures on the fund-month level using a trailing estimation period of 60 trading days.[9]

The *standard deviation* (STD) of daily fund returns is measured for a fund's largest share class over a period. The standard deviation is calculated as follows:

$$\sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t-\bar{r})^2}\,,$$

where T equals 60 days, r_i is the return of day t, and $\bar{r}$ is the mean return for the fund over the last 60 trading days.

Idiosyncratic risk (IDIO) is measured as the standard deviation of the residual of a market model regression and is calculated as follows:

$$\sqrt{\frac{1}{T-2}\sum_{t=1}^{T}\varepsilon_t^2}\,,$$

[9] Even though we concentrate on large funds, the daily returns of our top 100 funds show some stale net asset values (compare with Mamaysky, Spiegel, and Zhang, 2008). We use the trade-to-trade methodology by Dimson (1979) as a robustness check and obtain qualitatively similar results, which are available from the authors upon request.

where ε_t is the estimated error from a market model regression of daily fund returns r_t in excess of the risk-free rate $r_{f,t}$ on a constant and the daily excess returns of the Barclays U.S. Aggregate Bond Index $r_{m,t} - r_{f,t}$:

$$(r_t - r_{f,t}) = \alpha + \beta(r_{m,t} - r_{f,t}) + \varepsilon_t. \tag{1}$$

Beta risk (BETA) is measured by the β coefficient of the market model regression in equation (1).

Skewness (SKEW) measures whether the return distribution is skewed to the left (negative values) or skewed to the right (positive values). It is defined as follows:

$$\frac{\frac{1}{T}\sum_{t=1}^{T}(x_i-\bar{x})^3}{\left[\frac{1}{T}\sum_{t=1}^{T}(x_i-\bar{x})^2\right]^{1.5}}$$

Kurtosis (KURT) measures whether the return distribution exhibits fat tails.

$$\frac{\frac{1}{T}\sum_{t=1}^{T}(x_i-\bar{x})^4}{\left[\frac{1}{T}\sum_{t=1}^{T}(x_i-\bar{x})^2\right]^{2}}$$

Monthly raw return (RETURN) measures the monthly raw fund returns using the CRSP returns of the largest share class per fund.

The *manipulation-proof performance measure* (MPPM) is defined by Ingersoll, Spiegel, Goetzmann, and Welch (2007) as follows:

$$\frac{1}{(1-\rho)\Delta t}\ln\left(\frac{1}{T}\sum_{t=1}^{T}\left[(1+r_t)/(1+r_{f,t})\right]^{-\rho}\right),$$

where Δt equals 1/360 and ρ is the risk-aversion parameter, which we set to 3.[10]

Market model alpha (1*ALPHA*) is the α coefficient of the market model regression in (1).

Three-factor model alpha (3*ALPHA*) is the α coefficient of the Fama-French model that consists of the excess return of the stock market over the risk free asset, and the HML and SMB factors (e.g., Elton, Gruber, Agrawal, and Mann, 2001).

[10] The chosen level of risk aversion corresponds to the baseline value used by Ingersoll, Spiegel, Goetzmann, and Welch (2007).

The *four-factor model alpha* (4*ALPHA*) is based on Cici and Gibson (2012). It is based on specification (1) which is extended by the excess return of the stock market, a default factor, and a mortgage market factor[11].

The *five-factor model alpha* (5*ALPHA*) is based on Fama and French (1993). It is based on the three-factor model, which is extended by a default factor and a term structure factor.

3. Results

Table 1 shows the summary statistics for the top 100 corporate bond funds. With mean and median TNAs of $5.4 billion and $2.3 billion, respectively, these funds are large by any measure. Nevertheless, the dispersion of fund sizes is large and highly skewed, ranging from 204 million to over 92 billion. By far the largest 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 reason why there appear to be a number of "smaller" funds among the top 100 is that some funds experienced significant losses and redemptions during the financial crisis in 2008.[12] Note that the smallest of the top 100 funds in 2004 had a TNA of $1 billion.

[Table 1 about here]

The average fund age (since inception) among the top 100 bond funds is 22 years, ranging from as little as 4 years to 75 years. About 75% of the top 100 funds belong to a

[11] Barclays provides two versions of the GNMA index; one index with a maturity of 30 years and one index with a maturity of 15 years. It is not clear which index Cici and Gibson (2012) are using. We use the yield spread between the Barclays GNMA 30 year index and the risk-free rate because the 30 year index is the more commonly used index in practice. Results do not change if we use the yield spread between the Barclays GNMA 15 year index and the risk-free rate instead.

[12] These redemptions were especially pronounced among high-yield bond funds. At least 75% of these funds experienced fund outflows during the sample period, while outflows occurred only in 25% of investment grade funds.

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] There is significant variation in the average five-year probability of default (PD), which ranges from 0.13% to 35.18%. Thus, high-yield bond funds play an important role in our sample.

Most important to our analysis, we find that about 64% of funds are managed by a team of two or more fund managers, which is consistent with Pool, Stoffman, and Yonker (2012). Females are rare among fund managers. There is only one woman among our 35 single-manager funds, and only 18% of team-managed funds include at least one female in their management teams.

Figure 1 shows the evolution of the BBB yield spread over our sample period. While the spread remains relatively stable until 2007, it rises sharply during the financial crisis, especially after the collapse of Lehman Brothers in 2008. In the post-crisis period, the yield spread falls significantly, and remains relatively stable after late 2009.

[Figure 1 about here]

Of course, the BBB yield spread was not the only market characteristic that changed during the financial crisis. Other yield spreads changed too, and the liquidity of many high-risk securities dried up. For the purpose of this paper, we consider all of these changes as exogenous, i.e., not caused by the behavior of corporate bond funds. Furthermore, we assume that fund managers did not begin to use CDS because they forecasted the dramatic change in market conditions as a result of the financial crisis, which seems reasonable given that most funds were net sellers of credit protection. This allows us to investigate whether funds that used CDS were able to navigate a challenging market environment more successfully than funds that did not use CDS.

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

CDS can be used for a variety of strategies, which can have very different risk and return implications. For example, if a fund enters into short CDS positions, then this strategy increases the fund risk (ceteris paribus) and lowers the fund returns during times of increasing credit spreads. If a fund enters into long CDS positions, this strategy should improve the fund returns during times of increasing credit spreads, ceteris paribus. Panel B of Table 1 shows that the majority of the large corporate bond funds have been using CDS. CDS usage increased from 21% in 2004 to a maximum of 64% in 2008, and has stabilized at slightly below 50% since then.[14] The annualized turnover of CDS positions was 32% on average and suggests that many fund managers use CDS for market-timing rather than for hedging strategies. On average, 69% of the funds were net short in CDS and the total notional value of all CDS positions represented about 7.3% of TNAs.[15] In addition, Figure 2 shows the evolution of the average CDS long and short positions over our sample period from 2004 to 2010. The average CDS long position, measured by the notional value of all long CDS positions over a fund's TNAs, rose from less than 1 to about 3.5% before the onset of the crisis. During the crisis, it peaked at around 4.5%, and it declined in the post-crisis period. Given the strong increase in credit risk premia during the crisis, these strategy changes are consistent with some fund managers using CDS to hedge credit risk.

[Figure 2 about here]

Short CDS positions changed more dramatically, however. They increased from about 2% of TNAs in 2004 to 4% just before the onset of the crisis. They continued to increase to about 9% during the crisis, and declined only after early 2008. Given that credit spreads rose during the crisis period and declined in the post-crisis period, these changes in CDS short

[14] The time-series variation in CDS usage is not shown in the table but is available from the authors upon request.
[15] We show the winsorized values for CDS turnover and the notional values on the 0.5/99.5% level to take care of outliers.

positions should have had a negative impact on fund performance in both the crisis and the post-crisis period in general. These developments also show up in the net notional amount of TNAs. We observe the lowest ratio in February 2008 and thus a few months before Lehman's collapse.

3.1 Determinants of the Use of CDS

In this section, we first examine which funds are more likely to use CDS, in order to compare our results with the existing literature on derivatives usage by mutual funds. We distinguish between team-managed and single-manager funds because Almazan, Brown, Carlson, and Chapman (2004) find that more constraints with regard to derivatives usage are placed on funds that are managed by a team rather than a single manager. Using a probit regression, we estimate the following regression specification,

$$CDS_{it} = \alpha_t + \beta\, Team + \theta' X_{it} + \epsilon_{it}, \tag{2}$$

where *CDS* is a dummy variable that equals one if fund *i* used CDS in quarter *t* and zero otherwise; *Team* equals one if the fund was managed by more than one manager and zero otherwise; the vector *X* includes control variables; α_t denotes time fixed effects on the quarter level.

Since the prior literature has also shown that the use of derivatives by mutual funds is related to the fund size, membership of a fund family, fund age, fund expenses, and asset turnover, we include these variables in our analysis. We also control the regression for the fraction of a fund's TNAs 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. In addition, we distinguish between investment grade and high-yield funds, which may differ in their propensity to use CDS.

[Table 2 about here]

The first column in Table 2 reports the marginal effects from a pooled probit model using the CDS dummy as the dependent variable. The results show that team managed funds are about 18% less likely to use CDS than funds that are managed by a single manager, which may be a reflection of the additional investment restrictions imposed on teams, but it is also consistent with Baer, Kempf, and Ruenzi (2011) who find that teams tend to choose less extreme investment strategies than single managers.

Consistent with Koski and Pontiff (1999), we find that the use of CDS is positively correlated with membership of a larger fund family, the turnover ratio, the share of institutional investors, and the investment grade category. Funds that belong to a large fund family are about 24% more likely to use CDS than funds that do not belong to a large fund family. This suggests that economies of scale are one important determinant of CDS usage because the costs of setting up a CDS trading desk can be shared across several funds within one fund family. In addition, more active funds are also more likely to use CDS. The larger is the share of institutional investors, the higher is the likelihood that a fund will use CDS. This suggests that small institutional investors may use mutual funds, possibly to gain (indirect) access to CDS.

We further find that investment grade funds are about 24% 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 the 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 with their junk-rated bond positions (80.1%), on average.[16] Thus, investment grade funds are not only more likely to use CDS, but they are also more prone to invest in riskier reference names. In contrast to earlier studies, however, we find no size effect in our sample, probably because we focus on just the largest bond funds.

Since CDS can be short or long, we examine the determinants of being net long or net short for those funds that use CDS. We define a dummy variable *Net short*, which takes the value 1 if fund *i* is net short over all the value-weighted CDS positions in quarter *t* and zero otherwise. We thus replace the dependent variable of specification (2) with *Net short*. The probit regression results are shown in column 2. Most notably, funds managed by female fund managers are around 22% less likely to be net short in CDS, which may be a reflection of the higher risk-aversion of women relative to men. In contrast, team-managed funds are not more prone to be net short in CDS relative to solo-managed funds. Funds that belong to a big fund family are around 29% more likely to be net short on average. Thus, these funds are not only more likely to use CDS, but they are also more likely to be net short.[17]

3.2 The Use of CDS and Fund Performance

Panel A of Table 3 shows the descriptive statistics of all risk and performance measures. The standard deviation of daily raw returns (*STD*) was 1.19% per month, while the average raw return (*RETURN*) was 0.44% per month. The average and median alphas are all positive.

[16] These results are not reported in the tables, but are available from the authors upon request.
[17] We also estimate specifications with further explanatory variables, such as fund flow, average PD, net cash ratio, Form N-SAR score, or Morningstar rating. None of these variables enter the CDS usage/net short regressions significantly.

However, the four-factor alpha (4*ALPHA*) was close to zero, which implies that the average fund performance is explained by the stock market, the default and the mortgage factors.

[Table 3 about here]

In Table 3, Panel B, we report the average risk and performance measures for the crisis and non-crisis periods separately. All measures indicate that during the crisis period, funds' return distributions were very different compared to non-crisis periods. During the crisis, the fund returns were more volatile due to more idiosyncratic risk, negative extreme returns were more likely (left-skewed) and the overall return distributions had fatter tails. All performance measures indicate worse performance for corporate bond funds during the crisis. The differences are dramatic and statistically significant on any conventional level.

Next, we examine whether there are performance differences between the funds that were using CDS and those that were not. Using an OLS regression, we estimate the following specification

$$Y_{it} = \alpha_c + \beta_1 Crisis + \beta_2 CDS + \beta_3 (CDS * Crisis) + \theta' X_{it} + \epsilon_{it} \qquad (3)$$

where Y_{it} denotes the various performance measures; *Crisis* identifies the crisis period as defined by Ben-David, Franzoni, and Moussawi (2012); CDS equals one if fund *i* used CDS in month *t* and zero otherwise; the vector *X* includes the control variables of Panel A of Table 1; α_c denotes fund category fixed effects. The coefficient of interest is β_3, which provides the interaction effect of CDS usage during the crisis.

The results in Table 4 confirm that there were significant risk and performance differences during the crisis and the two non-crisis periods.[18] However, we observe no significant risk and performance differences between CDS users and CDS non-users. CDS

[18] Note that we do not distinguish between the two non-crisis periods but rather contrast the crisis period with both the non-crisis periods in all the analyses below. We omit estimates for all the control variables – the fund characteristics of Table 1, Panel A – due to space constraints.

users exhibit slightly higher systematic risk (*BETA*). In terms of performance, only the four-factor and five-factor alphas indicated that CDS users outperformed non-users. But the economic magnitude is small with 9-11 basis points per month. During the crisis period, CDS users underperformed non-users, but the economic magnitude is small (19 basis points per month based on the four-factor alpha) and the result is not robust based on the other risk-performance measures.

[Table 4 about here]

3.3 Teams versus Single Managers

In this section, we examine some of the costs and benefits of teams versus single managers in asset management. Our first hypothesis states that when executing complex strategies, i.e., those involving CDS, team-managed funds outperform solo-managed funds during normal market condition. In contrast, our second hypothesis postulates that in rapidly changing market conditions, e.g., during financial crises, the slower decision-making of teams reduces the performance of team-managed funds.

In order to test these hypotheses, we augment specification (3) with further interaction terms and estimate the following OLS regression

$$Y_{it} = \alpha_c + \beta_1 Crisis + \beta_2 CDS + \beta_3 Team + \beta_4 (Team * Crisis) + \beta_5 (CDS * Crisis) + \beta_6 (CDS * Team) + \beta_7 (CDS * Crisis * Team) + \theta' X_{it} + \epsilon_{it}, \quad (4)$$

where all variables are defined as in equations (2) and (3). Our first hypothesis implies $(\beta_3 + \beta_6) > 0$, while our second hypothesis implies $(\beta_3 + \beta_4 + \beta_6 + \beta_7) < 0$. We test both hypotheses using Wald tests.

[Table 5 about here]

The results in Table 5 show that team-managed funds that are using CDS perform better than solo-managed funds using CDS during normal market conditions. The second Wald test in Table 5 indicates a performance premium of 19-50 basis points per month. This performance premium is driven by both higher returns and lower risk. In contrast, among funds not using any CDS strategies, there are no significant performance differences between team-managed and solo-managed funds outside the crisis.[19] These results show that the greater diversity of expertise, experience and skill of teams relative to a single manager is valuable to investors only if the fund is using complex strategies during normal market conditions. These results confirm the first hypothesis.

During the financial crisis, however, the performance premium of teams that use CDS is negative (see third row of Wald tests in Table 5). In fact, teams underperform single managers by 31-70 basis points per month. In contrast, among funds not using any CDS strategies, there are again no significant performance differences between team-managed and solo-managed funds.[20] These results confirm our second hypothesis and show that teams perform poorly in adverse market conditions when employing complex strategies.[21] This could be due to the slower decision times of teams, which would be costly during times of rapidly changing market conditions. Decision times are, of course, not directly observable. However, we can examine some of the actual investment decisions of teams during the crisis and non-crisis periods. The return volatilities and idiosyncratic risk measures shown in Table 5, already suggest that team-managed and solo-managed funds have pursued different investment strategies during the crisis. Team-managed funds using CDS exhibited significantly higher return volatilities than solo-managed funds using CDS.

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[19] See the results for the *Team* coefficient. Note that we do not display a Wald test for this case because there is no combination of coefficients needed.

[20] Some of the performance measures indicate that team-managed funds outperform solo-managed funds, but the statistical significance is weak (see first row of Wald tests in Table 5).

[21] Unreported results suggest that team managed funds also underperform single managed funds during the crisis if they use other complex trading strategies, such as debt options or interest rate futures, as well. These results are available from the authors upon request.

We examine some of the CDS strategies more precisely in Table 6. In particular, we focus on the likelihood to be net short in CDS and the use of CDS on asset-backed securities, which experienced dramatic value losses during the financial crisis. The results in Table 6 show that teams were less likely to be net short CDS outside the crisis, and more likely to be net short CDS during the crisis. Given that credit spreads rose significantly during the crisis, being net short CDS during this time was the wrong position and can explain some of the losses experienced by team-managed funds during the crisis.

Furthermore, the results also show that team-managed funds had larger short positions in CDS on asset-backed securities than solo-managed funds during the crisis. Given the dramatic value losses on asset-backed securities during the financial crisis those CDS positions must have generated significant losses for team-managed funds. Overall, these results show that teams tended to be on the wrong side of the market during the crisis period.

Finally, we analyze the short-term market-timing skills of teams versus single managers using CDS. In Figure 2, we observed significant changes in a fund's long and short notional CDS positions over our entire sample period. In addition, we observe significant cross-sectional differences in CDS usage. The average net notional CDS amount ranged from as little as -57.9% of TNAs to a maximum of 22.9% of TNAs (see Panel B of Table 1). If a manager increased a fund's net short CDS position before credit spreads fell and decreased a fund's net short position before credit spreads rose, then this strategy should yield performance improvements ceteris paribus.

To examine managers' short-term market timing skills using CDS more rigorously, we determine the correlation between changes in funds' net CDS positions, measured by the net notional amount over a fund's TNA, and credit spreads over the next 1–3 months. Specifically, we run the following OLS regression

$$Net\ notional\ amount_{it}/TNA_{it} = \alpha_i + \beta_1 Spread_{t+n} + \theta' X_{it} + \varepsilon_{it}, \quad (4)$$

where *Spread* is measured by the BBB (or AAA) corporate yield spread over U.S. treasuries of month t+1 (or t+3), α_i are fund fixed effects, and X includes a vector of time-varying control variables. A positive coefficient β_1 indicates market-timing skill.

Table 7, Panel A presents the regression results for the entire sample period. The coefficients on the spread variables are between -0.56 and -1.61, and are statistically significant. They indicate that increases in the net short CDS position are followed by increases in credit spreads over the next 1–3 months. This implies that these adjustments to a fund's net CDS position must have had a negative impact on fund performance. Our findings are in line with those of Comer, Boney, and Kelly (2009), who find poor market-timing ability for high-quality bond funds, but are in contrast with those of Chen, Ferson, and Peters (2010), who find neutral to weakly positive market-timing ability for bond mutual funds.

[Table 7 about here]

Next, we analyze the market-timing skills of teams and single managers separately, by adding an interaction term *Spread* * *Team* to equation (4). Note that the individual *Team* variable was part of the control variables X in Panel A. The results are reported in Panel B of Table 7. We find that the negative short-term market timing effect is primarily present in team-managed rather than solo-managed funds, which implies that it is mostly teams who exhibit poor market timing skills. Finally, we examine managers' market timing skills for the crisis and non-crisis periods separately. The results in Table 7, Panel C show that teams exhibit poor market timing skills especially during the crisis period, not during the non-crisis periods. These results are consistent with the poor performance of teams that employ CDS strategies during the crisis as shown in Table 5. The results do not, however, explain why teams performed relatively better during non-crisis periods. Therefore, this outperformance must be due to reasons other than superior market timing capabilities. For example, being net short CDS generated fee income outside the crisis, which may have contributed to the relatively better performance of teams during non-crisis periods.

In summary, our results show that teams made a number of wrong investment decisions involving the use of CDS during the crisis period, which at least partially explain the poor performance of team-managed funds during this time.

4. Conclusion

In this paper, we analyze the use of credit default swaps by the largest 100 U.S. corporate bond funds between 2004 and 2010. We find that the use of CDS increased from about 20% of funds in 2004 to over 60% of funds in 2008 and stabilized at about 50% after the crisis. The size of a fund's total CDS position (measured by CDS notional values) is usually less than 10% of a fund's TNAs, but some funds exceed this level by a wide margin, especially during the financial crisis. Overall, funds are net sellers of CDS, which shows that fund managers do not use CDS to hedge credit risk on average. The high turnover of CDS positions also suggests that many fund managers use CDS for market-timing rather than for hedging strategies.

We find that if funds made use of complex trading strategies involving CDS, team-managed funds outperform solo-managed funds during normal market conditions. This may be due to the greater diversity of expertise, experience and skill of teams relative to a single manager, which should be especially valuable if a fund is using a diversity of complex trading strategies. In contrast, during the financial crisis the performance premium of teams becomes negative. This is because during this time, team-managed funds made especially poor investment decisions involving CDS. These results indicate that while teams have some advantages over single managers during normal market conditions, the less efficient decision-making processes of teams can be costly during adverse market conditions.

References

Adams, J.C., T. Nishikawa, and R.P. Rao, 2013, Mutual Fund Performance, Management Teams, and Boards, unpublished working paper.

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.

Baer, M., A. Kempf, and S. Ruenzi, 2011, Is a Team Different from the Sum of its Parts? Evidence from Mutual Fund Managers, *Review of Finance* 15, 359–396.

Barry, C.B., and L.T. Starks, 1984, Investment Management and Risk Sharing with Multiple Managers, *Journal of Finance* 39, 477–491.

Ben-David, I., F. Franzoni, and R. Moussawi, 2012, Hedge Fund Stock Trading in the Financial Crisis of 2007–2009, *Review of Financial Studies* 25, 1–54.

Bliss, R., M. Potter, and C. Schwarz, 2008, Performance Characteristics of Individual vs. Team Managed Mutual Funds, *Journal of Portfolio Management* 34, 110–119.

Cao, C., E. Ghysels, and F. Hatheway, 2011, Derivatives Do Affect Mutual Fund Returns: Evidence from the Financial Crisis of 1998, *Journal of Futures Markets* 31, 629–658.

Chen, J., H. Hong, M. Huang, and J.D. Kubik, 2004, Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization, *American Economic Review* 94, 1276–1302.

Chen, Y., W. Ferson, and H. Peters, 2010, Measuring the Timing Ability and Performance of Bond Mutual Funds, *Journal of Financial Economics* 98, 72–89.

Cici, G., 2012, The Prevalence of the Disposition Effect in Mutual Funds' Trades, *Journal of Financial and Quantitative Analysis* 47, 795–820.

Cici, G., and S. Gibson, 2012, The Performance of Corporate Bond Mutual Funds: Evidence Based on Security-Level Holdings, *Journal of Financial and Quantitative Analysis* 47, 159–178.

Cici, G., and L.-F. Palacios, 2013, On the Use of Options by Mutual Funds: Do they Know What they are Doing? Unpublished working paper.

Comer, G., V. Boney, and L. Kelly, 2009, Timing the Investment Grade Securities Market: Evidence from High Quality Bond Funds, *Journal of Empirical Finance* 16, 55–69.

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

Dimson, E., 1979, Risk Measurement When Shares Are Subject to Infrequent Trading, *Journal of Financial Economics* 7, 197–226.

Elton, J.E., M.J. Gruber, D. Agrawal, and C. Mann, 2001, Explaining the Rate Spread on Corporate Bonds, *Journal of Finance* 56, 247–277.

Fama, E.F., and K.R. French, 1993, Common Risk Factors in the Return of Stocks and Bonds, *Journal of Financial Economics* 33, 3–56.

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

Ingersoll, J., M. Spiegel, W. Goetzmann, and I. Welch, 2007, Portfolio Performance Manipulation and Manipulation-Proof Performance Measures, *Review of Financial Studies* 20, 1503–1546.

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.

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

Mamaysky, H., M. Spiegel, and H. Zhang, 2008, Estimating the Dynamics of Mutual Fund Alphas and Betas, *Review of Financial Studies* 21, 233–264.

Marin, J.M., and T. Rangel, 2006, The Use of Derivatives in the Spanish Mutual Fund Industry, unpublished working paper, University Pompeu Fabra.

Meng, L., and O. ap Gwilym, 2007, The Characteristics and Evolution of Credit Default Swap Trading, *Journal of Derivatives & Hedge Funds* 13, 186–198.

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.

Patel, S., and S. Sarkissian, 2014, To Group or Not to Group? Evidence from CRSP, Morningstar Principia, and Morningstar Direct Mutual Fund Databases, unpublished working paper.

Pool, V.K., N. Stoffman, and S.E. Yonker, 2012, No Place Like Home: Familiarity in Mutual Fund Manager Portfolio Choice, *Review of Financial Studies* 25, 2563–2599.

Prather, L.J., and K.L. Middleton, 2002, Are N + 1 Heads better than one? The Case of Mutual Fund Managers, *Journal of Economic Behavior & Organization* 47, 103–120.

Sharpe, W. F., 1981, Decentralized Investment Management. *Journal of Finance* 36, 217–234.

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

Vroom, V.H., 2003, Educating Managers for Decision Making and Leadership, *Management Decision* 41, 968–978.

Figure 1: Spread development

Yield spread between the BBB-rated corporate bonds and the risk-free rate. The data are taken from the Fed website. The pre-crisis period ranges from 2004M07 to 2007M06, the crisis period follows Ben-David, Franzoni, and Moussawi (2012) and spans from 2007M07 to 2009M03, while the post-crisis period includes 2009M04 to 2010M12.

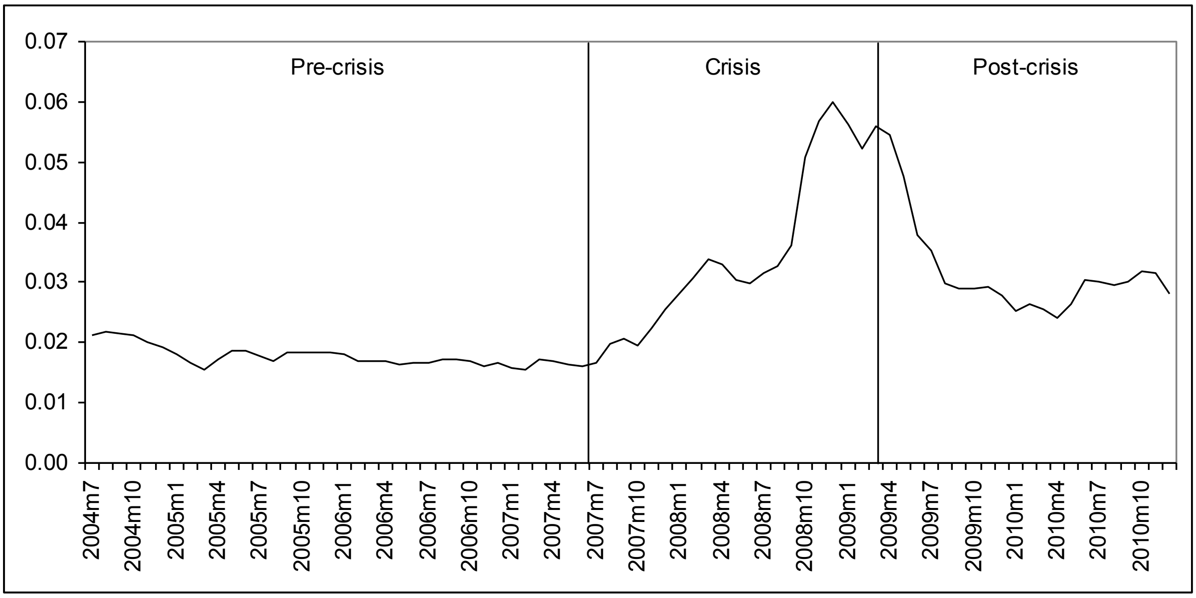

Figure 2: Development of CDS usage intensity and direction

The figure shows the size of long (solid line), short (dotted line), and net (dashed line) CDS positions for CDS-using funds, measured by the ratio of CDS notional amounts over a fund's TNAs. All values are winsorized on the 0.5/99.5%. The pre-crisis period ranges from 2004M07 to 2007M06, the crisis period follows Ben-David, Franzoni, and Moussawi (2012) and spans from 2007M07 to 2009M03, while the post-crisis period includes 2009M04 to 2010M12.

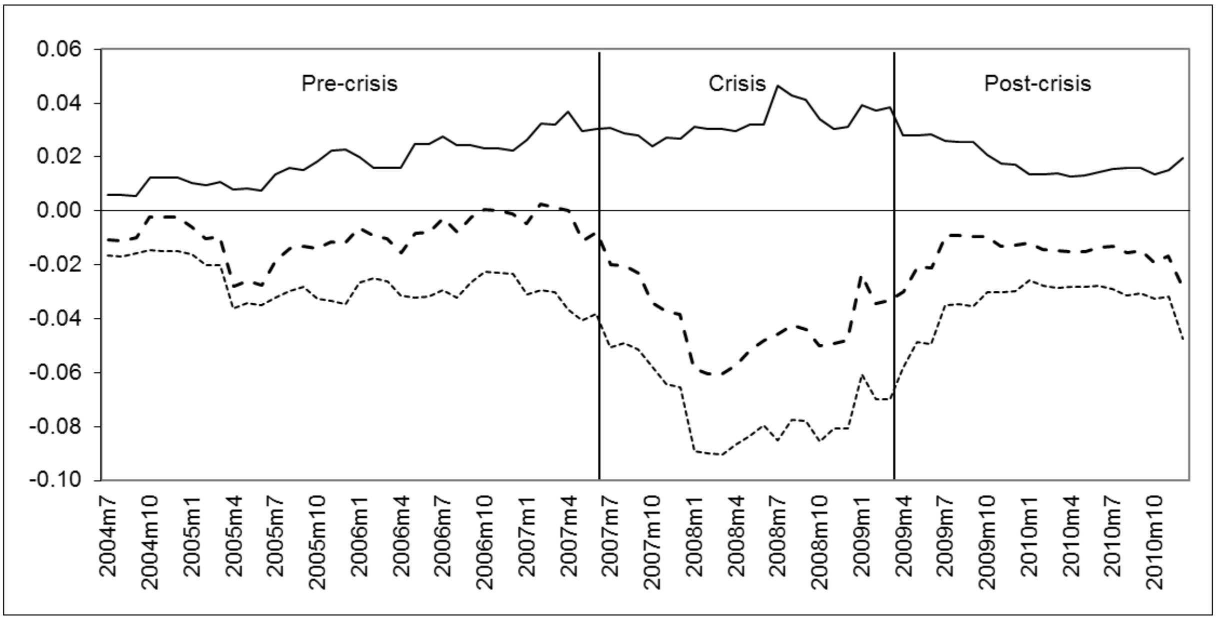

Table 1: Fund characteristics and CDS usage

Panel A shows the fund characteristics of the top 100 U.S. mutual corporate bond funds between 2004Q3 and 2010Q4. The data are on the fund-quarter level, yielding 26 observations per fund, except for five funds that were merged with other funds and observations with missing values in at least one necessary variable. The top 100 funds are defined as the largest (by TNAs) 100 corporate bond funds in the CRSP survivorship-free mutual fund database 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. The first five categories are investment grade, while the latter two are below investment grade. *Team* is a dummy variable that equals 1 if the fund is managed by two or more managers and 0 otherwise. *Female* is a dummy variable that equals 1 if at least one woman was involved in managing the fund in the respective quarter. *TNA* denotes a fund's total net assets. *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. *Fund age* measures the number of years since a fund's inception. *Expense ratio* is the sum of a fund's operating expenses (including 12b-1 fees, waivers, and reimbursements) over a fund's TNAs. *Turnover ratio* is defined as the minimum of aggregated sales and purchases of securities divided by the 12-month average TNAs. *Institutional investors* is the proportion of a fund's TNA held by institutional investors (net assets of institutional investor fund classes/TNAs). *Investment grade* is a dummy variable that equals 1 for investment grade funds and 0 for high-yield funds. *Monthly fund flow* is measured by $(TNA_t – TNA_{t-1}(1 + \text{monthly fund return}_t))/TNA_{t-1}$. We approximate credit risk by weighting a bond's credit ratings by the average, cumulative five-year default frequency (*Average PD*). *Net cash ratio* is the net cash (cash minus liabilities) over a fund's TNAs. The *Form N-SAR score* ranges between 0 and 4. The score sums up four dummy variables that take the value 1 if the fund is engaged in repos, debt options, interest futures, or borrowing and 0 otherwise. *Morningstar rating* is the numerical Morningstar rating. The data are from the CRPS survivorship-free mutual fund database, Morningstar, Moody's Ratings, and the SEC's Edgar. Panel B provides the CDS usage characteristics. The data are from the SEC's Edgar and from EdgarOnline. *CDS* is a dummy variable that equals 1 if a fund used CDS in the respective quarter and 0 otherwise. *Net short* equals 1 if a fund's CDS positions were net short on average in the respective quarter and 0 otherwise. *CDS turnover* is the annualized CDS turnover. The last four variables are TNA-weighted CDS intensity measures, using either the total notional amount of all CDS positions, the net notional amount of all CDS positions, or only the short or long positions.

Panel A: Fund characteristics

Variable	Mean	SD	Min.	p50	Max.	N
Team (dummy)	0.644	0.479	0.000	1.000	1.000	2,554
Female (dummy)	0.181	0.385	0.000	0.000	1.000	2,554
TNA	5,414	11,221	204	2,315	92,875	2,554
Big fund family (dummy)	0.746	0.435	0.000	1.000	1.000	2,554
Fund age (in years)	22	10	4	20	75	2,554
Expense ratio	0.779	0.342	0.132	0.741	1.724	2,554
Turnover ratio	1.417	1.534	0.150	0.820	10.070	2,554
Institutional investors	0.334	0.387	0.000	0.125	1.000	2,554
Investment grade (dummy)	0.611	0.488	0.000	1.000	1.000	2,554
Monthly fund flow	-0.002	0.024	-0.069	-0.002	0.058	2,554
Average PD (in percent)	8.057	8.819	0.132	2.376	35.180	2,554
Net cash ratio (in percent)	9.783	14.283	-50.730	7.075	68.815	2,554
Form N-SAR score	1.256	0.840	0.000	1.000	4.000	2,554
Morningstar rating	3.391	0.963	1.000	3.000	5.000	2,554

Panel B: CDS usage

Variable	Mean	SD	Min.	p50	Max.	N
CDS (dummy)	0.4475	0.4973	0.0000	0.0000	1.0000	2,554
Net short (dummy)	0.6850	0.4647	0.0000	1.0000	1.0000	1,143
CDS turnover	0.3178	0.6095	0.0000	0.0050	4.0000	1,143
Net notional amount / TNA	-0.0222	0.0852	-0.5785	-0.0069	0.2294	1,143
Notional amount / TNA	0.0725	0.1371	0.0002	0.0294	1.0142	1,143
Short notional amount / TNA	-0.0461	0.0959	-0.6965	-0.0172	0.0000	1,143
Long notional amount / TNA	0.0244	0.0535	0.0000	0.0047	0.4010	1,143

Table 2: Determinants of CDS usage

This table reports the marginal effects of the probit regressions. The dependent variable in the first column, *CDS*, is a dummy variable that equals 1 if fund *i* used CDS in quarter *t* and 0 otherwise. For the second column, *Net short* equals 1 if a fund's CDS positions were net short on average in the respective quarter and 0 otherwise. Refer to Table 1 for a description of the sample selection process and the variable definitions. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the fund level and are reported in parentheses.

Variable	CDS (dummy)	Net short (dummy)
Team	-0.1777**	-0.0830
	(0.0825)	(0.1038)
Female	-0.1341*	-0.2205***
	(0.0799)	(0.0685)
TNA	-0.0013	0.0026
	(0.0036)	(0.0017)
Big fund family	0.2398**	0.2926***
	(0.0913)	(0.1029)
Fund age	0.0069	-0.0027
	(0.0044)	(0.0035)
Expense ratio	0.1681	-0.0610
	(0.1694)	(0.1448)
Turnover ratio	0.0672*	-0.0130
	(0.0399)	(0.0213)
Institutional investors	0.2928**	0.0603
	(0.1166)	(0.1125)
Investment grade	0.2358**	-0.1364
	(0.0956)	(0.0877)
Time FE	Yes	Yes
N	2,554	1,143
Adj. R square	0.1915	0.0877

Table 3: Distribution of risk-performance measures

Panel A shows the distribution of risk-performance measures of the top 100 funds. Refer to Table 1 for the sample selection process. We use the daily CRSP fund returns of the largest share class per fund. All the measures are on a monthly basis if appropriate. *STD* is the standard deviation of the fund returns. *IDIO* is the unsystematic risk measured by the standard deviation of the residual terms of the market model regression, which is a regression of the daily fund returns in excess of the risk-free rate on a constant and the daily returns of the Barclays U.S. Aggregate Bond Index in excess of the risk-free rate. *BETA* is the systematic risk measured by the beta coefficient of the market model regression. *SKEW* is the skewness of the fund returns. *KURT* is the excess kurtosis of the fund returns. *RETURN* is the monthly raw fund returns. *MPPM* is a manipulation-proof performance measure. 1*ALPHA* is the market model alpha measured by the constant of the market model regression. 3*ALPHA* is the alpha of the Fama-French three-factor model. 4*ALPHA* is the alpha of the four-factor model using the aggregate bond market, the stock market, a default factor, and a mortgage market factor (Cici and Gibson, 2012). 5*ALPHA* is the alpha of the five-factor model that extends the Fama-French three factor model by a default factor and a term structure factor (Fama and French, 1993). Panel B shows the average risk-performance measures by non-crisis and crisis period (2007M07–2009M03) following Ben-David, Franzoni, and Moussawi (2012). The non-crisis period consists of the pre- (2004M07–2007M06) and post-crisis periods (2009M04–2010M12). We use a t-test with unequal variances for the differences between the crisis and the non-crisis periods. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Distribution

Variable	Mean	SD	Min.	p50	Max.	N
STD	0.0119	0.0074	0.0026	0.0098	0.0504	7,264
IDIO	0.0084	0.0072	0.0015	0.0060	0.0502	7,264
BETA	0.5863	0.4940	-0.5502	0.6179	2.6090	7,264
SKEW	0.3304	0.7338	-1.5806	0.2294	2.8532	7,264
KURT	4.3424	2.0373	2.0799	3.7616	15.053	7,264
RETURN	0.0044	0.0195	-0.1080	0.0056	0.0783	7,264
MPPM	0.0044	0.0226	-0.1362	0.0050	0.0785	7,264
1FALPHA	0.0021	0.0213	-0.1340	0.0011	0.0790	7,264
3FALPHA	0.0047	0.0211	-0.1152	0.0049	0.0731	7,264
4FALPHA	0.0006	0.0069	-0.0364	0.0008	0.0208	7,264
5FALPHA	0.0035	0.0147	-0.0830	0.0022	0.0502	7,264

Panel B: Averages by period

Period	STD	IDIO	BETA	SKEW	KURT	RETURN	MPPM	1FALPHA	3FALPHA	4FALPHA	5FALPHA
Non-crisis	0.0098	0.0066	0.5953	0.4468	4.5214	0.0073	0.0093	0.0070	0.0085	0.0019	0.0064
Crisis	0.0182	0.0136	0.5599	-0.0081	3.8224	-0.0041	-0.0096	-0.0120	-0.0066	-0.0034	-0.0049
Difference	0.0085***	0.0070***	-0.0354***	-0.4549***	-0.6991***	-0.0114***	-0.0189***	-0.0190***	-0.0151***	-0.0053***	-0.0112***

Table 4: Determinant of fund performance: CDS usage

This table shows the OLS regression results with respect to the CDS usage decision of the top 100 funds. Refer to Table 1 for the sample selection process. The dependent variables are the risk-performance measures as defined in Table 3. *Crisis* equals 1 for the crisis period (2007M07–2009M03) and 0 otherwise. *CDS* equals 1 if fund *i* used CDS in quarter *t* and 0 otherwise. The control variables include the fund characteristics of Panel A of Table 1. We use fund category fixed effects according to the seven Lipper fund classes that are described in Table 1. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the fund level and are reported in parentheses.

Variable	STD	IDIO	BETA	SKEW	KURT	RETURN	MPPM	1FALPHA	3FALPHA	4FALPHA	5FALPHA
Crisis	0.0081***	0.0069***	-0.0657***	-0.4402***	-0.8453***	-0.0114***	-0.0185***	-0.0189***	-0.0141***	-0.0041***	-0.0099***
	(0.0006)	(0.0006)	(0.0188)	(0.0538)	(0.1540)	(0.0014)	(0.0023)	(0.0022)	(0.0018)	(0.0007)	(0.0010)
CDS	0.0006	0.0006	0.0395*	0.0183	0.0366	-0.0003	0.0003	-0.0005	0.0013	0.0009***	0.0011*
	(0.0004)	(0.0004)	(0.0232)	(0.0660)	(0.1475)	(0.0006)	(0.0010)	(0.0009)	(0.0010)	(0.0003)	(0.0006)
CDS * Crisis	0.0000	-0.0002	0.0240	-0.0471	0.1649	0.0012	0.0000	0.0008	-0.0015	-0.0019**	-0.0022
	(0.0008)	(0.0009)	(0.0241)	(0.0665)	(0.1850)	(0.0018)	(0.0030)	(0.0028)	(0.0024)	(0.0009)	(0.0015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264
Adj. R square	0.3764	0.4269	0.7172	0.1502	0.1954	0.1048	0.1719	0.1980	0.1486	0.1653	0.1935

Table 6: Determinants of CDS usage – Crisis interaction

This table reports the marginal effects of a probit regression (first column) and the OLS results (second column). The dependent variable in the first column, *Net short* equals 1 if a fund's CDS positions were net short on average in the respective quarter and 0 otherwise. For the second column, *Net notional of ABS reference names / TNA* equals the sum of the net notional amounts of CDS with asset back securities (ABS) reference names over the funds' TNA. The independent variables include the fund characteristics of Panel A of Table 1 and additionally the *CDS turnover* in the second column. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the fund level and are reported in parentheses.

Variable	Net short (dummy)	Net notional - ABS reference names / TNA
Crisis	-0.1106	-0.0006
	(0.0862)	(0.0011)
Team	-0.2604***	0.0011
	(0.0780)	(0.0013)
Team * Crisis	0.1999**	-0.0083**
	(0.0678)	(0.0038)
Regression	Probit	OLS
Control variables	Yes	Yes
Fund category FE	Yes	Yes
N	1,143	1,143
Adj. R square	0.1367	0.1285

Table 7: Market timing

This table shows the market-timing regression results. The data are on the fund-month level. Panel A provides the results for the general effect. We estimate OLS regressions with *Net notional amount/TNA* as the dependent variable and BBB (columns 1 and 2) and AAA corporate credit spreads (columns 3 and 4) over treasuries of month *t*+1 and respectively *t*+3 as the main independent variables. The yield data are taken from the Fed website. The time-varying control variables include ln(*TNA*), ln(*Fund age*), expense ratio, turnover ratio, share of institutional investors, team managed, female fund manager, average PD of bonds, average share junk-rated bonds, net cash ratio, Morningstar rating, monthly fund flows, and *CDS turnover*. We also use fund fixed effects. Panels B shows the differential effect with respect to team management. Panel C repeats the Panel B analysis by using observations from the pre- and post-crisis period only. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the fund level and are reported in parentheses.

Panel A: General effect

Variable	(I)	(II)	(III)	(IV)
Type of spread:	BBB $Spread_{t+1}$	BBB $Spread_{t+3}$	AAA $Spread_{t+1}$	AAA $Spread_{t+3}$
$Spread_{t+n}$	-0.5566*	-0.6422*	-1.5143**	-1.6111**
	(0.3225)	(0.3661)	(0.6803)	(0.7908)
Time-varying control variables	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes
N	3,444	3,444	3,444	3,444
R square	0.1640	0.1664	0.1673	0.1687

Panel B: Differential effect with respect to team management

Variable	(I)	(II)	(III)	(IV)
Type of spread:	BBB $Spread_{t+1}$	BBB $Spread_{t+3}$	AAA $Spread_{t+1}$	AAA $Spread_{t+3}$
$Team_t$	0.0415*	0.0527**	0.0525*	0.0633**
	(0.0229)	(0.0238)	(0.0266)	(0.0284)
$Spread_{t+n}$	0.2546	0.4372	0.3514	0.6992
	(0.4038)	(0.3513)	(0.7970)	(0.7258)
$Spread_{t+n}$ * $Team_t$	-1.3215*	-1.7450**	-3.1913*	-3.9462**
	(0.7863)	(0.7929)	(1.8165)	(1.8860)
Time-varying control variables	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes
N	3,444	3,444	3,444	3,444
R square	0.1741	0.1848	0.1800	0.1886

Panel C: Differential effect with respect to team management – pre- and post-crisis periods only

Variable	(I)	(II)	(III)	(IV)
Type of spread:	BBB $Spread_{t+1}$	BBB $Spread_{t+3}$	AAA $Spread_{t+1}$	AAA $Spread_{t+3}$
$Team_t$	0.0178	0.0183	0.0142	0.0132
	(0.0230)	(0.0313)	(0.0197)	(0.0221)
$Spread_{t+n}$	0.3787	0.8399	0.9525	1.1840
	(0.5430)	(0.7762)	(0.9155)	(0.9259)
$Spread_{t+n}$ * $Team_t$	-0.3384	-0.4381	-0.4560	-0.4224
	(0.8996)	(1.3362)	(1.3846)	(1.6167)
Time varying control variables	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
N	2,222	2,222	2,222	2,222
R square	0.1090	0.1108	0.1115	0.1125

Table 5: Determinant of fund performance: CDS usage – Differential effect with respect to team management

The table shows the OLS regression results of the CDS usage decision and the differential effect with respect to team management of the top 100 funds. Refer to Table 1 for the sample selection process. The dependent variables are the risk-performance measures as defined in Table 3. *Crisis* equals 1 for the crisis period (2007M07–2009M03) and 0 otherwise. *CDS* equals 1 if fund *i* used CDS in quarter *t* and 0 otherwise. *Team* is a dummy variable that takes the value 1 if fund *i* was managed by a team in quarter *t* and 0 otherwise. The Wald tests provide additional results for various combinations of individual coefficients testing team- versus solo-managed funds. The control variables include the fund characteristics of Panel A of Table 1. We use fund category fixed effects according to the seven Lipper fund classes that are described in Table 1. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Standard errors are clustered at the fund level and are reported in parentheses.

Variable	STD	IDIO	BETA	SKEW	KURT	RETURN	MPPM	1FALPHA	3FALPHA	4FALPHA	5FALPHA
Crisis	0.0093***	0.0086***	-0.1207**	-0.5201***	-0.8461***	-0.0138***	-0.0237***	-0.0243***	-0.0169***	-0.0051***	-0.0121***
	(0.0013)	(0.0014)	(0.0557)	(0.0908)	(0.3030)	(0.0027)	(0.0046)	(0.0042)	(0.0036)	(0.0012)	(0.0020)
CDS	0.0012*	0.0013**	0.0287	0.1616	0.2955	-0.0015	-0.0025	-0.0037***	-0.0009	-0.0007	-0.0009
	(0.0007)	(0.0006)	(0.0384)	(0.1019)	(0.2404)	(0.0010)	(0.0016)	(0.0014)	(0.0018)	(0.0006)	(0.0010)
Team	-0.0006	0.0000	-0.0930*	0.1709	0.3440	-0.0002	0.0001	-0.0005	0.0009	-0.0001	0.0005
	(0.0007)	(0.0005)	(0.0524)	(0.1032)	(0.2521)	(0.0007)	(0.0013)	(0.0011)	(0.0013)	(0.0004)	(0.0008)
Team * Crisis	-0.0016	-0.0023	0.0768	0.1066	-0.0055	0.0034	0.0072	0.0076	0.0039	0.0014	0.0030
	(0.0016)	(0.0016)	(0.0617)	(0.1109)	(0.3372)	(0.0029)	(0.0049)	(0.0047)	(0.0040)	(0.0014)	(0.0024)
CDS * Crisis	-0.0025*	-0.0036**	0.0710	-0.0046	-0.0169	0.0075**	0.0126**	0.0131**	0.0086*	0.0027*	0.0051*
	(0.0015)	(0.0015)	(0.0626)	(0.1175)	(0.3464)	(0.0032)	(0.0054)	(0.0050)	(0.0045)	(0.0014)	(0.0027)
CDS * Team	-0.0010	-0.0012	0.0154	-0.2246*	-0.4141	0.0021**	0.0049***	0.0055***	0.0040**	0.0028***	0.0035***
	(0.0008)	(0.0007)	(0.0493)	(0.1201)	(0.2925)	(0.0010)	(0.0017)	(0.0014)	(0.0020)	(0.0007)	(0.0011)
CDS * Crisis * Team	0.0038**	0.0051***	-0.0639	-0.0372	0.3140	-0.0097***	-0.0192***	-0.0187***	-0.0157***	-0.0072***	-0.0113***
	(0.0018)	(0.0018)	(0.0709)	(0.1403)	(0.3957)	(0.0035)	(0.0059)	(0.0056)	(0.0050)	(0.0017)	(0.0031)
Wald tests: Team- vs solo-managed funds											
During the crisis, no CDS usage	-0.0022	-0.0023	-0.0162	0.2775***	0.3385	0.0032	0.0073*	0.0071*	0.0048	0.0013	0.0035*
Outside the crisis, with CDS usage	-0.0016**	-0.0012*	-0.0776**	-0.0537	-0.0701	0.0019**	0.0050***	0.0050***	0.0049***	0.0027***	0.0040***
During the crisis, with CDS usage	0.0006	0.0016*	-0.0647*	0.0157	0.2384	-0.0044**	-0.0070**	-0.0061**	-0.0069***	-0.0031***	-0.0043***
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264	7,264
Adj. R square	0.3790	0.4320	0.7176	0.1551	0.1968	0.1074	0.1799	0.2061	0.1562	0.1823	0.2013

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