Original Article

Bond mutual funds and complex investments

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ABSTRACT We are the first to analyze bond mutual funds' permission and use of complex investments such as derivatives, restricted securities, and securities lending. Based on unique regulatory information from the SEC's N-SAR filings, we show that most complex investments do not affect fund performance or risk. However, interest rate futures (IRF) are harmful to bond funds. Bond funds engaging in IRF (46.94% of all bond funds) underperform nonusers by economically meaningful 54 basis point of alpha p.a. Our results reveal that bond funds employ IRF for speculation as they increase funds' exposure toward interest rate risk.

Keywords: mutual fund performance; bond funds; performance; derivatives; interest rate futures
JEL Classification: G11; G12

INTRODUCTION AND LITERATURE OVERVIEW

In this paper, we are the first to analyze the effects of complex instruments such as derivatives, restricted securities, short selling, otherwise obtaining leverage, and security lending on the performance and risk characteristics of bond mutual funds. This subject is of vital importance as the total assets under management of US domestic bond funds in 2015 were $2104 billion, a substantial growth from $831 billion a decade earlier, underlining their growing importance for the US economy.[1] Moreover, the investment practices of mutual funds in general have recently attracted the attention of the US Security Exchange Commission (SEC) in their concern that such practices might jeopardize investors' money or even destabilize the whole financial system. Thus, the SEC examination priorities for 2016 are concerned with analyzing mutual fund complex instruments use.[2] The primary focus of the existing literature regarding complex investment practices, however, has focused on equity funds while there is next to no research on bond funds. We close this gap using unique and comprehensive data on the instrument use of 997 US domestic bond funds for the period from 1999 to 2014 obtained from the SEC's N-SAR filings merged with fund characteristics from the CRSP mutual fund database.

Complex investment restrictions of equity funds have been examined by Almazan *et al* (2004). They find no performance difference between lowly and highly constrained funds. Similarly, Clifford *et al* (2014) show that loosening investment restrictions has no implications for equity fund performance. Lynch-Koski and Pontiff (1999), Frino *et al* (2009), Cao *et al* (2011), Cici and Palacios (2015), Rohleder *et al* (2017) and Natter *et al* (2016) analyze how the use of derivatives affects equity mutual fund performance and risk characteristics with different results. Chen *et al* (2013) find that short selling may act as a skill proxy for equity funds. Evans *et al* (2016) relate equity funds lending of securities to their performance and find that lenders underperform non-lenders.

Bond funds, however, might be influenced by the use of complex investments in a different way than equity funds since risk and return profiles for bonds differ from those of stocks (see, e.g., Chen and Qin, 2016). In this context, our summary statistics show that the use of complex instruments is more common among bond funds compared to equity funds. Specifically, more than 49% of bond funds use derivatives of some kind compared to only 36% of equity funds (Rohleder *et al*, 2017, Table 2). The difference is even more dramatic for futures with almost 47% users among bond funds compared to only 23% among equity funds. Moreover, we find that 36% of bond funds use leverage of some kind, for example, 15% through short selling compared to only 7% of equity funds (Chen *et al*, 2013, Figure 2). Further, 47% of our bond funds use security lending or repos (65%) compared to 43% of equity funds using security lending (Evans *et al*, 2016, Table 2). Thus, it seems that complex investments are more important for bond funds than for equity funds.

However, the use of such instruments by bond funds has been scarcely analyzed. To our knowledge, there exist only two studies examining very specific questions, Deli and Varma (2002) and Adam and Guettler (2015). The former find that transaction cost savings are the main drivers for the permission to invest in derivatives based on form N-SAR ("Semi-annual report")[3] filings in the short examination period from 1997Q1 to 1998Q2.[4] Adam and Guettler (2015) show that the use of credit default swap (CDS) has a positive impact on corporate bond fund performance for single manager funds in crisis periods and for team managed funds during normal times. Their findings are based on N-CSR ("certified annual shareholder report") filings and N-Q ("quarterly schedule of portfolio holdings") filings of the 100 largest corporate bond funds during the period 2004–2010. Apart from that, the majority of academic research on bond mutual funds, starting with the seminal paper of Blake *et al* (1993), analyze bond fund performance and generally find that bond funds underperform their benchmarks (e.g., Elton *et al*, 1995; Ferson *et al*, 2006; Huij and Derwall, 2008). Although of great importance to both regulators and investors, the question of how bond funds actually invest has not garnered much academic attention. Among the few, Cici and Gibson (2012) as well as Huang and Wang (2014) use security-level holdings data to analyze bond funds' picking and timing skills.

In our empirical analysis, we use a unique dataset containing regulatory information on complex investment permissions and usage for 997 actively managed US domestic bond funds during the period 1999–2014 to show that bond funds frequently use complex investments. The data used in this paper are obtained from individual N-SAR filings downloaded from the SEC's "Electronic Data Gathering, Analysis, and Retrieval" (EDGAR) database and merged with fund returns and characteristics from the CRSP Survivor-Bias-Free Mutual Fund Database and represents the largest CRSP/N-SAR bond fund sample to date. Based on this data, we show that overall complex investment permissions and engagement do not have significant impact on performance. Funds' use of interest rate futures (IRF), however, negatively affects fund performance, leading to (risk-adjusted) underperformance of IRF users by economically meaningful 54 basis points per year. As 46.94% of all bond funds use IRF at least once, this finding at least partially explains the underperformance of bond mutual funds found in the existing literature. The results further show that bond funds employ IRF to increase their average portfolio duration and thus increase their exposure to changes in interest rates, indicating that they employ interest rate futures to speculate on interest rate changes. As these results may be driven by other fund characteristics, performance model choice, or omitted variables, we explicitly control for alternative explanations by carrying out a multitude of robustness tests.

The rest of the paper is structured as follows. The second section describes our data and performance measurement methodology. The third section describes the main empirical results while the fourth section presents alternative explanations and further tests. The fifth section concludes.

DATA AND METHODOLOGY

Sample construction

One reason for the lack of research on bond funds' complex investments is that data on complex investment use are not readily available in standard mutual fund databases. However, according to the Investment Company Act (ICA) of 1940, funds have to disclose their permission to use and their actual use of non-standard investment practices in semiannual N-SAR filings with the SEC from which we obtain unique and previously unused information on permission and engagement in such practices.[5,6] Although several studies use N-SAR filings for the analysis of equity mutual funds, their use in bond fund analysis is rare.[7]

We construct our final sample as follows. We select all funds with a CRSP objective indicating general, corporate, or government bond funds, i.e., funds with CRSP objective codes "I" or starting with "IC" and "IG," respectively.[8] Subsequently, we eliminate all index funds flagged by CRSP or identified via name search as in Amihud and Goyenko (2013). We focus on the period of 1999–2014, as daily return data necessary for calculating time-varying performance and risk measures are only available in the CRSP database since September 1999.[9] Funds are only considered once they cross the threshold size of $5 million in total net assets (TNA) as in Fama and French (2010) to control for fund incubation (Evans, 2010) and if they have at least 12 monthly observations.[10]

For information on complex investments, we gather N-SAR filings stored in individual text filings on the SEC's EDGAR database and merge them with the CRSP mutual fund database.[11] Following Natter *et al* (2016), we use algorithmic string matching techniques to match funds by their names. This approach leads to a correlation of total net assets (TNA) and turnover variables available from both CRSP and N-SAR of 99% and 89%, respectively, implying an unbiased sample.[12] Furthermore, Table 11 in "Appendix" shows no substantial differences in descriptive statistics of bond funds available in the merged sample and all actively managed domestic bond funds available in the CRSP database.

Overall, we merge 8569 N-SAR filings with information of actively managed domestic bond funds available in CRSP.[13] This leads to a final dataset consisting of 997 individual bond funds with 15,252 unique semiannual observations, making it the most comprehensive merged N-SAR/CRSP bond fund sample including regulatory data on complex investments to date. Overall, the merged sample between CRSP and N-SAR covers 65.28% of all bond funds and 67.77% of all bond fund TNA in the CRSP mutual fund database making it a good representation of the bond fund universe.

Variable definition

We derive dummy variables on complex investments from Item 70 of a fund's N-SAR filing. Item 70 asks whether or not a fund has permission to use various complex investments during the semiannual reporting period and whether a fund actually employs the respective complex investment during the reporting period or not. We focus on the following complex investment practices relevant to bond mutual funds. Item 70C regards the writing or investing in options on debt securities. Item 70E asks for writing or investing in interest rate futures, and item 70G regards the writing or investing in options on futures. These activities make up the derivatives category. Item 70J reports investment in restricted securities.[14] Items 70O, 70Q, and 70R focus on borrowing of money in excess of 5% of a fund's TNA, margin purchases, and short selling, respectively, and are consolidated into the leverage category. Finally, item 70A and item 70N state whether the respective fund is permitted to use (uses) repos and securities lending, respectively.

Unfortunately, it is not possible to discriminate funds according to the degree of their usage, as the SEC's N-SAR filings do not provide data on the amount or market value of most complex investments. However, this should bias our results against finding any impact of complex investments, as the potential relation of complex investments with fund characteristics is easier to detect for heavy users than for light users.

Further information on fund characteristics and returns is mainly from the CRSP mutual fund database. CRSP only reports data at share class level. Hence, to obtain fund-level data, we aggregate all variables by value weighing each share class by its respective TNA. TNA is the sum of individual share class TNA. Fund age is the age of the oldest share class, while load information is based on the largest share class. Manager tenure is the time the longest tenured manager is affiliated with the fund. We identify funds as retail (institutional) funds if at least 50% of TNA is in share classes targeted at retail (institutional) investors. Family TNA is the sum of TNA of all funds with the same management code reported by CRSP. Cash is the percentage of TNA held in actual cash or cash equivalents by the fund, and net flow is calculated as implied investor net flow as a fraction of TNA.

Performance measurement

This paper is concerned with the relation between complex investments and fund performance and risk. As investment decisions may change, it is important to consider time-varying fund performance and risk. Moreover, funds might adjust their risk-return profiles by using complex investments such as derivatives, which also could result in time-varying risk exposure. Hence, we calculate performance and risk for each semi-annual fund reporting period based on daily returns. We use gross returns as they represent returns generated by bond fund investment decisions and thus better capture the behavior of fund managers (e.g., Fama and French, 2010; Pastor *et al*, 2015).[15] To measure bond funds' risk-adjusted performance, we use the following factor regression model based on Fama and French (1993) and Cici and Gibson (2012):

$$\begin{aligned} \mathrm{er}_{i,d,t} = \alpha_{i,t}^{4-f} &+ \beta_{\mathrm{TERM},i,t}\mathrm{TERM}_{d,t} \\ &+ \beta_{\mathrm{DEF},i,t}\mathrm{DEF}_{d,t} + \beta_{\mathrm{opt},i,t}\mathrm{OPT}_{d,t} \\ &+ \beta_{\mathrm{mkt},i,t}\mathrm{MKTRF}_{d,t} + \varepsilon_{i,d,t}.^{16,17} \end{aligned} \tag{1}$$

where $\mathrm{er}_{i,d,t}$ is fund *i*'s daily gross fund return in excess of the 1-month US T-Bill rate and $\alpha_{i,t}^{4-f}$ is fund *i*'s risk-adjusted performance during reporting period *t*. $\mathrm{TERM}_{d,t}$ is the return difference between the Barclays Capital Intermediate Government Bond Index and the 1-month US T-Bill rate and captures returns generated by increasing duration, i.e., higher interest rate risk.[18] $\mathrm{DEF}_{d,t}$ is the return difference between the Barclays Capital US High Yield and US Intermediate Government indices and captures returns generated by taking on higher default risk. The option factor $\mathrm{OPT}_{d,t}$ captures nonlinearities due to investment in mortgage-backed securities and is measured by the return difference between the Barclays Capital US Mortgage Backed Securities and US Intermediate Government indices. To control for possible equity exposure of bond funds, for example, through the investment in convertible bonds, $\mathrm{MKTRF}_{d,t}$ measures the excess return of the CRSP value-weighted market index (e.g., Comer and Rodriguez, 2013).[19] As we implement the estimates of our performance regressions as dependent as well as independent variables in panel regressions, all these estimated performance and risk measures are winsorized at the 1 and 99% percentiles, respectively, following standard procedure in the empirical financial literature (e.g., Fama and French, 2008; Coles *et al*, 2008; Pontiff and Woodgate, 2008).[20]

EMPIRICAL ANALYSIS OF COMPLEX INVESTMENTS

Descriptive statistics of bond fund characteristics

Table 1 shows fund-by-fund descriptive statistics of bond fund characteristics. The average (median) bond fund has \$1039 million (\$229 million) in assets under management indicating many small and few exceptionally large funds. Family size is similarly distributed with few large families and many small families. The funds are on

Table 1: Summary statistics

	Mean	*Median*	*SD*
Fund characteristics			
TNA ($mil)	1039	229	5666
Family TNA ($mil)	107,225	26,505	247,338
Age (years)	11.3	9.7	8.2
Manager tenure (years)	6.5	5.6	4.1
Turnover ratio (% TNA, p.a)	156.07	93.85	183.36
Load dummy (%)	63.89	100.00	48.06
Retail fund dummy (%)	52.21	60.27	46.17
Expense ratio (% TNA, p.a)	0.83	0.78	0.37
Cash (% TNA)	4.51	3.61	14.98
Net flow (% TNA)	0.74	0.30	2.37
Fund performance and risk			
Excess gross return (% p.a.)	3.76	3.65	1.12
Excess net return (% p.a.)	2.94	2.88	1.08
Volatility (% p.a.)	4.83	3.94	3.17
4-factor alpha (gross) (% p.a.)	0.39	0.28	2.48
4-factor alpha (net) (% p.a.)	−0.41	−0.45	2.48
TERM beta (%)	58.81	57.66	30.00
DEF beta (%)	8.32	3.58	10.91
OPT beta (%)	27.82	25.84	18.90
MKT beta (%)	1.25	0.18	3.52

Notes: This table presents mean, median, and standard deviation of fund characteristics for 997 actively managed domestic bond funds with entries in N-SAR filings and the CRSP mutual fund database during the period 1999–2014.

average 11.3 years old and managed by managers with an average tenure of 6.5 years. Turnover, as measured by the annual average turnover ratio of 156.07%, is higher than in studies of equity funds due to the constant requirement to rebalance portfolios when bonds mature.

Nearly two-thirds of the sample bond funds (63.89%) charge loads to their customers upon buying or selling fund shares and half of all funds (52.21%) mainly cater to retail investors. Average yearly expense ratios of 0.83% are substantially smaller than for equity funds. Similar to equity funds, bond funds hold a considerable fraction of their assets in the form of cash (4.51% on average). Over the course of the sample period, bond funds experience an average monthly net flow of nearly 0.74% documenting the growth of the bond fund market over the past 15 years. While mean excess gross and net returns (3.76 and 2.94% per year) as well as average gross alphas are positive (0.39% per year), net-of-fee alphas are negative (−0.41% per year) which is in line with the existing literature, e.g., Elton *et al* (1995), Huij and Derwall (2008) as well as Cici and Gibson (2012). The TERM beta is positive on average with a mean of 0.5881 and median of 0.5766 implying that bond funds generate returns by earning term premia. The DEF beta is also positive with a mean (median) of 0.0832 (0.0358) indicating that bond funds also generate returns with default spread strategies. Moreover, our sample funds' returns seem to correlate substantially with the mortgage-backed securities factor indicated by a mean exposure of 0.2782. However, the bond funds in our sample do not take on substantial equity exposure as the exposures to the respective factor are small. The exposures to the term and default factor as well as to the mortgage factor vary substantially between funds, as indicated by the high standard deviations of these factors (30.00, 10.91, and 18.90%, respectively).

Complex investment permission and use

Complex investments may play a minor role for bond funds since investors often seek bond funds as conservative investments, whereas complex investments may increase

Table 2: Complex investment permission and use

	Panel (a) Cross section		*Panel (b) Semiannual*			
	Permission	*Use*	*Permission*	*Use*	*Permission changes*	*Usage changes*
Derivatives	92.78	49.65	89.45	33.56	2.33	7.10
Bond options	90.17	20.66	85.45	7.13	2.99	3.61
Interest rate futures	89.87	46.94	84.93	31.06	3.56	6.75
Futures options	89.47	22.27	84.80	10.42	3.36	3.38
Leverage	97.79	36.41	92.62	12.33	6.84	6.84
Borrowing money	95.69	26.98	87.54	7.25	3.56	4.75
Margin purchases	30.79	1.50	19.32	0.37	3.18	0.20
Short selling	69.11	14.54	52.39	5.53	5.37	2.76
Restricted securities	95.29	75.13	94.28	57.77	1.75	9.49
Repos	99.20	64.79	98.62	47.12	0.69	8.48
Security lending	94.98	47.44	93.00	31.54	2.43	6.76

Notes: This table shows descriptive statistics (in %) on complex investment permission and use of bond mutual funds. The sample consists of actively managed domestic bond funds over the period 1999–2014 with N-SAR filings and entries in the CRSP mutual fund database. In Panel (a), permission (use) reports the percentage of all funds that are allowed to use (use) the respective complex investment at least once during the sample period. In Panel (b), permission (use) indicates the percentage of all semiannual fund reporting periods when funds are permitted to use (use) the respective complex investment. Permission (usage) changes shows the fraction of all observations in which permission to use (use) changed.

risk. On the other hand, bond funds may seek non-standard yield opportunities. Particularly, in the highly competitive environment of the mutual fund industry, complex investments may be used by some bond funds to gain an advantage over competitors. To get a first impression of bond funds' complex investments, Panel (a) of Table 2 displays cross-sectional statistics of permission and use of non-standard investment practices. The majority of bond funds have permission to use derivatives, invest in restricted securities, obtain leverage by borrowing money, or to use other complex investments, such as security lending and repurchase agreements (repos). However, not all funds with the permission to employ complex investments make use of this opportunity. For example, although 92.78% of all funds have the permission to use derivatives, only 49.65% actually engage in these instruments at least once over the sample period. Regarding derivatives, bond funds mainly use interest rate futures as nearly half of the sample funds (46.94%) employ them at least once. These numbers are significantly higher than those reported for US equity funds by, e.g., Rohleder *et al* (2017). Options on bonds (20.66%) and futures (22.27) are less common. Nevertheless, they are also used by a fifth of all funds. These numbers are in line with equity option (Natter *et al*, 2016).

By borrowing money in excess of 5% of their TNA, 26.98% of bond funds obtain leverage. Attaining leverage via margin purchases is forbidden for the majority of bond funds similar to results for equity funds in Almazan *et al* (2004). Short selling is allowed for 69.11% of all sample funds, and 14.54% use this opportunity during the sample period, compared to 7% short sale users reported by Chen *et al* (2013) for equity funds. In contrast to Almazan *et al* (2004) and in line with Clifford *et al* (2014) for equity funds, there are nearly no restrictions on investments in restricted securities. Hence, the majority of funds invest in this security type (75.13%) implying at least partially illiquid holdings. Nearly, all funds (99.20%) have the permission to engage in repos and 64.79% of sample funds make use of this permission. Half of the funds employ securities lending (47.44%), in line with findings by Evans *et al* (2016) for equity funds.

Panel (b) of Table 2 shows pooled statistics on the percentage of time funds have permission to use (actually use) complex investments. Similar to the findings for equity

Table 3: Tobit regression of complex investment permission and engagement score

	Permission score	*Engagement score*
Log TNA	0.0184**	0.0546***
	(2.44)	(8.22)
Log family TNA	0.0549***	0.0579***
	(7.21)	(8.21)
Age	−0.0212***	−0.0000
	(3.53)	(0.00)
Manager tenure	−0.0160***	−0.0092*
	(2.61)	(1.72)
Turnover ratio	0.0149***	0.0381***
	(3.55)	(4.97)
Load dummy	0.0293**	0.0201
	(2.21)	(1.55)
Retail dummy	−0.0390***	−0.0086
	(2.94)	(0.67)
Expense ratio	0.0154**	0.0019
	(2.55)	(0.30)
Cash	−0.0095*	−0.0123***
	(1.82)	(2.66)
Net flow	−0.0042	−0.0068**
	(1.64)	(2.52)
Performance	0.0013	−0.0012
	(0.49)	(0.42)
Government	−0.0749***	−0.1586***
	(4.91)	(9.61)
Corporate	0.0135	−0.0208
	(0.86)	(1.32)
Time fixed effects	Yes	Yes
Cox-Snell R^2	0.198	0.274
N	13,977	13,977

Notes: This table shows results of a pooled panel tobit regression of complex investment permission and engagement score on fund characteristics. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. The dependent variable permission (engagement) is the weighted average score of all individual complex investment permission (engagement) dummies. Performance is measured with the 4-factor alpha. All explanatory variables are standardized and lagged one period. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. Absolute *t* values based on standard errors clustered by fund are given in parentheses.

funds by Almazan *et al* (2004), bond funds do not constantly use the respective complex investments. Only restricted securities are employed in more than half (57.77%) of all fund months. All other complex investments are used more sporadically. This could be a result of tactical decision making by bond funds with respect to their complex investments. The statistics on usage changes further support this notion as bond funds engagement changes between 0.2 and 9.5% of the time. Permissions do not change considerably. These descriptive statistics thus show that complex investments are an important aspect of bond fund investment behavior and that some practices, especially the use of futures, are even more prevalent in bond funds than in equity funds.

Determinants of complex investments permission and use

According to statistics presented in Table 2, bond mutual funds' permission and engagement in complex investments vary between funds. Therefore, this section analyzes the drivers of complex investment permission and use. As possible determinants, we use lagged fund characteristics as reported in Table 1. To control for the potentially differential impact of different bond fund types, additional dummy variables indicating corporate and government bond funds are included as style-fixed effects.

Almazan *et al* (2004) argue that different complex investments may be substitutes for each other. For example, funds can obtain short positions via direct short selling of bonds or indirectly by having the appropriate position in an interest rate future or bond option. To assess the influence on overall complex investments permissions (use), we condense the information on individual bond fund permissions (use) into a permission (engagement) score. In the spirit of Almazan *et al* (2004), this permission (engagement) score is computed by calculating the average of the permission (engagement) dummies of the broad complex investment categories derivatives, leverage, restricted securities, and income.

As the dependent variables permission score and engagement score are continuous variables restricted to the range between 0 and 1, Table 3 shows the marginal effects of panel tobit regressions with time- and style-fixed effects. All continuous independent variables are standardized as in Clifford *et al* (2014) for ease of interpretation. Similar to Almazan *et al* (2004), the natural logarithm of fund size has a positive relation to a fund's permission score, with a coefficient of 0.0184. The same is true for funds belonging to larger families (coefficient of 0.0549). More experienced fund managers are less likely to have permission to invest into complex investments as indicated by the negative coefficient. This is in contrast to findings for equity funds' permissions to use options by Lynch-Koski and Pontiff (1999).

As in Deli and Varma (2002), bond funds' permission to invest into debt derivatives is positively related to their turnover (coefficient of 0.0149). Bond funds mainly catering to retail investors are less likely to have permission to invest in complex instruments. The coefficient on expense ratios is significantly positive with a coefficient of 0.0154, implying that the infrastructure necessary to use complex investments, such as sophisticated trading desks (e.g., Cici *et al*, 2015), risk management systems, back office personnel, and fund managers, is costly. In comparison with general and corporate bond funds, government bond funds are more restricted in their use of complex instruments, possibly due to the fact that these funds attract especially conservative investors.

Although not all funds with permission to use certain complex investments actually use them, the results for the engagement score as the dependent variable are very similar. Larger funds belonging to larger families with less experienced fund managers and higher turnover ratios use complex investments more intensively, echoing the results for equity fund's use of derivatives found by Rohleder *et al* (2017) and for securities lending by Evans *et al* (2016). For corporate bond funds, Adam and Guettler (2015) also find that belonging to a large family increases the likelihood of using CDS. Higher cash holdings are negatively related to a fund's engagement score indicating that complex instruments might serve as an alternative way to manage investor's liquidity demands (Rohleder *et al*, 2017). Lagged fund performance affects neither complex investment permission nor engagement score indicating that complex instruments permission and use are exogenously rather than endogenously determined. The Cox–Snell R^2s of the panel tobit regressions are 20 and 27%, respectively, indicating a good model fit.

Complex investments and fund performance

So far, we have shown that bond mutual funds commonly employ complex investments, especially if they are large, belong to large families, and have high turnover ratios. How these complex investments affect fund performance and risk characteristics is not clear a priori as existing studies for equity funds do not offer conclusive evidence. Almazan *et al* (2004) and Clifford *et al* (2014) find no relevant relation between complex investment restrictions and fund performance. Concerning derivatives, Lynch-Koski and Pontiff (1999) as well as Cici and Palacios (2015) find no significant differences between option user and nonuser equity funds regarding their performance and risk characteristics. Natter *et al* (2016), on the other hand, show that option user funds outperform nonuser funds at lower market risk. Frino *et al* (2009) and Rohleder *et al* (2017) show that funds use derivatives to mitigate the adverse effect of investor flows on equity fund performance. Chen *et al* (2013) show that equity funds using short sales have higher risk-adjusted performance than nonusers, both in long and short portfolios. Security lending or repurchase agreements may be employed as an additional income source. However, Evans *et al* (2016) find that equity funds lending securities underperform non-lenders. Regarding bond funds, Adam and Guettler (2015) are the only ones to analyze non-standard investments in the form of CDS for a limited sample of the largest 100 US corporate bond funds and find no overall performance impact.

To get a first impression of the performance impact of bond fund's complex investment permission and engagement, Panel (a) of Table 4 shows (risk-adjusted) performance of a hypothetical zero-investment portfolio which is long funds with permission (engagement) scores above the median score and short funds with permission (engagement) scores below the median during the previous reporting period.[21] However, the (risk-adjusted) gross returns of the differential portfolios are indistinguishable from zero indicating that aggregate complex instrument permission and use are not significantly related to performance, similar to findings of Almazan *et al* (2004).

Aggregated scores, however, may hide the effect of individual complex investments. Therefore, Panel (b) of Table 4 analyzes the individual components of the complex investment engagement score using hypothetical zero-investment portfolios, which are long funds using the specific investment practice and short funds not using them. As one would expect from the

Table 4: Complex investment portfolio sorts

	Panel (a) Complex investment scores		*Panel (b) Individual complex investments user vs. nonuser*								
	Permission score	*Engagement score*	*Bond options*	*Interest rate futures*	*Futures options*	*Borrowing money*	*Margin purchases*	*Short selling*	*Restricted securities*	*Repos*	*Security lending*
Return	0.0029	−0.0039	0.0011	−0.0047	0.0022	−0.0016	−0.0017	−0.0004	0.0031	0.0037*	0.0030*
	(0.76)	(−0.57)	(0.28)	(−1.19)	(0.51)	(−0.38)	(−0.23)	(−0.12)	(0.42)	(1.71)	(1.60)
4-factor alpha	−0.0011	0.0014	−0.0032	−0.0054**	−0.0036	−0.0021	−0.0087	−0.0039	−0.0012	0.0001	0.0008
	(−0.73)	(0.76)	(−1.07)	(−2.43)	(−1.03)	(−0.71)	(−1.05)	(−1.35)	(−0.72)	(0.13)	(0.42)

Notes: This table shows annual performance of portfolios sorted on complex investments. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. In Panel (a) funds are sorted into the long (short) portfolio each month when their permission (engagement) score during the lagged reporting period is above the median permission (engagement) score and into the short portfolio when the permission (engagement) score is below its median score. In Panel (b) funds are sorted into the long (short) portfolio if they are engaged (not engaged) in the respective complex investment during the lagged reporting period. Performance is measured with monthly raw gross fund returns and the 4-factor model. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. *t* values corrected for heteroskedasticity and serial correlation of up to four lags (Newey and West, 1987) are given in parentheses.

results of Panel (a), most complex investments' correlation with performance is indistinguishable from zero. Using interest rate futures (IRF), however, is significantly and negatively related to risk-adjusted performance of the differential portfolio. Bond funds engaging in IRF underperform bond funds without engagement in IRF by economically relevant 54 basis points on a yearly basis when we measure performance with the 4-factor model defined in equation (1). The leverage instruments borrowing of money, margin purchases, and short selling do not lead to any differences in performance. Thus, bond funds' short selling activities may not proxy for fund manager skill contrasting the findings for equity fund managers by Chen *et al* (2013). Restricted securities also have no clear relation to fund performance. Income-generating techniques, such as repos and lending of securities, significantly enhance gross returns, but do not offer any benefit on a risk-adjusted basis. However, they do not harm fund performance contrasting the findings for equity funds by Evans *et al* (2016).

Interest rate futures, fund performance, and interest rate risk

The underperformance of bond funds engaged in IRF shown in Table 4 may be influenced by fund characteristics other than derivatives use. Hence, we formally test the relation between bond fund performance and lagged IRF engagement with the following panel regression model including time-fixed effects:

$$\text{Performance}_{i,t} = \varphi_0 + \varphi_1 \text{IRF}_{i,t} + \sum_{j=2}^{J} \varphi_j \text{Controls}_{i,j,t} + \eta_{i,t}. \tag{2}$$

where performance$_{i,t}$ is fund i's risk-adjusted annualized performance in semiannual reporting period t measured with the 4-factor model defined in equation (1) and calculated using daily gross returns. IRF$_{i,t}$ is a dummy equal to one if fund i uses IRF during reporting period t.[22,23] Controls$_{i,j,t}$ are the fund characteristics reported in Table 1 and commonly associated with performance in the fund performance literature (e.g., Ferreira *et al*, 2012). Following Petersen (2009), we cluster standard errors by both fund and semiannual reporting period to control for heteroscedasticity and time series as well as cross-sectional correlation.

The results are displayed in Table 5. The univariate regression in column (1) shows a negative relation between engagement in IRF in reporting and risk-adjusted fund performance in period t. The coefficient of −86 basis points is economically substantial and significantly different from zero with a t value of −6.70. This indicates that funds investing in IRF underperform otherwise similar funds. The R^2 of this regression is 43% indicating a very good fit. When including fund control variables, the coefficient on IRF becomes −66 basis points (t value of −5.04). The coefficients on the control variables are in line with the existing literature. Fund size has a positive impact on performance overall, but a negative relation within a fund, implying diseconomies of scale (Chen *et al*, 2004). Surprisingly, a higher expense ratio shows a positive relation to fund performance in contrast to existing studies for equity funds (e.g., Carhart, 1997). This could be due to better managers obtaining the economic rents of a fund via higher fees (e.g., Berk and Green, 2004). Older funds underperform, while cash is positively related to fund performance similar to findings for equity funds by Simutin (2014).

To control for potential fund heterogeneity and a possible omitted variable bias, columns (3) and (4) additionally include style- and fund-fixed effects, respectively.[24] In both columns, the significant negative relation between IRF engagement and performance holds. Coefficients are −0.0062

Table 5: Performance and term risk regression

	Panel (a) Performance				Panel (b) Term beta			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
IRF	−0.0086***	−0.0066***	−0.0062***	−0.0030**	0.1204***	0.0681***	0.0553***	0.0092
	(−6.70)	(−5.04)	(−4.87)	(−2.09)	(6.15)	(3.62)	(3.14)	(1.13)
Log TNA		0.0004	0.0001	−0.0032***		0.0102	0.0123**	0.0011
		(0.92)	(0.34)	(−3.60)		(1.60)	(2.07)	(0.21)
Log family TNA		0.0008**	0.0007**	−0.0009		0.0039	0.0096**	0.0006
		(2.27)	(2.08)	(−1.32)		(0.80)	(2.05)	(0.10)
Age		−0.0000	0.0001*	−0.0004		0.0014	−0.0013	−0.0013
		(−0.12)	(1.80)	(−0.40)		(1.11)	(−1.19)	(−0.60)
Manager tenure		0.0001	0.0001	0.0000		−0.0036**	−0.0028*	−0.0023**
		(0.74)	(0.50)	(0.36)		(−2.15)	(−1.82)	(−2.55)
Turnover ratio		−0.0009***	−0.0008***	−0.0002		0.0241***	0.0226***	0.0025
		(−3.50)	(−3.09)	(−0.83)		(4.85)	(4.28)	(1.33)
Load dummy		−0.0007	−0.0008			−0.0175	−0.0106	
		(−0.58)	(−0.71)			(−0.77)	(−0.50)	
Retail dummy		−0.0019*	−0.0018*			−0.0031	−0.0068	
		(−1.66)	(−1.69)			(−0.13)	(−0.30)	
Expense ratio		1.0781***	0.9490***	0.4064		−3.8864	−1.3211	2.9898
		(3.64)	(3.42)	(0.90)		(−1.30)	(−0.48)	(1.21)
Cash		0.0125***	0.0123***	0.0129***		−0.0624	−0.0606	0.0216***
		(11.18)	(10.26)	(10.52)		(−0.79)	(−0.83)	(3.14)
Net flow		0.1872***	0.1870***	0.1608***		−0.2436*	−0.2690**	−0.1938***
		(8.40)	(8.27)	(6.50)		(−1.71)	(−2.03)	(−2.81)
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	No	No	Yes	No	No	No	Yes	No
Fund-fixed effects	No	No	No	Yes	No	No	No	Yes
Adj. R^2	0.43	0.45	0.46	0.49	0.09	0.12	0.21	0.77
N	15,252	15,252	15,252	15,252	15,252	15,252	15,252	15,252

Notes: This table shows results of a pooled panel regression of annual fund performance (Panel a) and term risk (Panel b) on interest rate future engagement. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. Performance (term beta) is the intercept (slope on the TERM factor) from the 4-factor model. Performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. IRF is a dummy variable equaling one when a fund uses interest rate futures in the respective reporting period and zero otherwise. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. *t* values based on standard errors two-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

(t value −4.87) and −0.0030 (−2.09), respectively, and imply a relevant economic magnitude for IRF users' underperformance. This indicates that bond funds do not profit from potential benefits of futures use, such as transaction cost savings as indicated by Deli and Varma (2002), but face losses instead.

The mechanisms leading to these losses, however, are not directly clear. On the one hand, bond funds may employ IRF to hedge their existing bond positions against changes in interest rates and thus against changes in bond prices by decreasing their portfolio duration.[25] In doing so, they may forgo performance potential associated with the term premium, but their returns may also be more independent from interest rate and thus bond market movements. If bond funds, on the other hand, use IRF to speculate on interest rate movements, they should have a higher exposure to changes in interest rates, i.e., a higher duration. Consequently, bond funds' exposure to the term factor may tell us more about their motives to employ IRF. If bond funds hedge their existing bond positions against changes in interest rates, parts of their existing interest rate sensitivity should be offset by their futures positions, i.e., their portfolio duration should be lowered by engaging in IRF. In this case, interest rate future users would have lower term betas. If they speculate on interest rate movements, this beta should be amplified implying that bond funds use IRF to increase their duration. To identify this behavior, Panel (b) of Table 5 measures the relation between time-varying interest rate risk and IRF engagement in the following panel regression with time-fixed effects:

$$\beta_{\mathrm{TERM},i,t} = \varphi_0 + \varphi_1 \mathrm{IRF}_{i,t} + \sum_{j=2}^{J} \varphi_j \mathrm{Controls}_{i,j,t} + \eta_{i,t}. \tag{3}$$

where $\beta_{\mathrm{TERM},i,t}$ is fund i's interest rate exposure in semiannual reporting period t measured with the 4-factor model defined in equation (1) and calculated using daily gross returns.[26] $\mathrm{IRF}_{i,t}$ and $\mathrm{Controls}_{i,j,t}$ are defined as in equation (2). Standard errors are clustered by both fund and semiannual reporting period following Petersen (2009).

Column (5) shows a positive coefficient of the IRF dummy. The coefficient of 0.1204 (t value 6.15) implies that IRF users exhibit a term risk exposure, which is 12 percentage points higher on average compared to nonusers. When including fund control variables, this coefficient changes to 0.0681, still economically substantial and significantly different from zero with a t value of 3.62. Hence, we conclude that bond funds do not use IRF to hedge against interest rate changes. Rather, they might employ IRF to speculate on changes in interest rates as using futures seems to be attended by higher portfolio durations. The result of a positive correlation between IRF employment and term risk also holds for style- and fund-fixed effects specifications in columns (7) and (8), although the coefficients with fund-fixed effects do not differ statistically from zero. Hence, the higher term risk is mainly a cross-sectional outcome.

ALTERNATIVE EXPLANATIONS AND FURTHER TESTS

Fees, using decisions and endogeneity

So far, our results are based on gross of fee returns as these better represent the investment decisions of fund managers. To analyze whether the underperformance of IRF users also translates to lower returns for bond fund investors, the net returns Panel (a) of Table 6 shows results for panel regressions similar to columns (3) and (7) of Table 5 using net of fee instead of gross returns. The coefficient of the IRF dummy is −62 basis points (0.0553) with a t value of −4.87 (3.14) for fund performance (term risk). This indicates that the

Table 6: Performance and term risk regression: alternative explanations

	Panel (a) Net returns		*Panel (b) Non-using*		*Panel (c) Endogeneity I*		*Panel (d) Endogeneity II*	
	Performance	*Term beta*	*Performance*	*Term beta*	*Performance*	*Term beta*	*Performance*	*Term beta*
IRF	−0.0062***	0.0553***	−0.0061***	0.0565***	−0.0054***	0.0521***	−0.0058***	0.0139***
	(−4.87)	(3.14)	(−4.45)	(3.00)	(−4.04)	(2.94)	(−4.47)	(2.66)
Non-using			0.0003	0.0069				
			(0.19)	(0.28)				
Performance					0.1283***	−0.8290***		
					(2.72)	(−5.69)		
Risk							−0.0089***	0.7870***
							(−3.25)	(37.85)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.45	0.21	0.46	0.21	0.48	0.22	0.48	0.70
N	15,252	15,252	15,252	15,252	13,977	13,977	13,977	13,977

Notes: This table shows results of a pooled panel regression of fund performance and term risk on interest rate future engagement. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. Performance (term beta) is the intercept (slope on the TERM factor) from the 4-factor model. For the net return Panel (a), performance and risk are calculated for each fund and semiannual reporting period individually using daily net of fee excess fund returns. For the other panels, performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. IRF is a dummy variable equaling one when a fund uses interest rate futures in the respective semiannual reporting period and zero otherwise. Non-using in Panel (b) is one if a user fund does not use interest rate futures in the respective semiannual reporting period and in all other cases zero. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. t values based on standard errors two-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

underperformance of bond funds using IRF is passed on to fund investors.

The results so far may not clearly show that it is the actual engagement in IRF that alters fund performance and interest rate risk. The negative (positive) relation between IRF engagement and fund performance (risk) might arise indirectly from general characteristics of IRF users. To test this, we employ the following augmented versions of equations (2) and (3):

$$\begin{aligned}\text{Performance}_{i,t} = \varphi_0 + \varphi_1\text{IRF}_{i,t} \\ + \varphi_2\text{NONUSING}_{i,t} \\ + \sum_{j=3}^{J}\varphi_j\text{Controls}_{i,j,t} + \eta_{i,t}.\end{aligned} \quad (4)$$

$$\begin{aligned}\text{Risk}_{i,t} = \varphi_0 + \varphi_1\text{IRF}_{i,t} \\ + \varphi_2\text{NONUSING}_{i,t} \\ + \sum_{j=3}^{J}\varphi_j\text{Controls}_{i,j,t} + \eta_{i,t}.\end{aligned} \quad (5)$$

where the dummy $\text{NONUSING}_{i,t}$ is one if an overall IRF user fund does not use IRF in semiannual reporting period t and zero otherwise (e.g., Natter *et al*, 2016).[27] The non-using Panel (b) of Table 6 shows that the coefficients on IRF do not change substantially compared with the main specification in columns (3) and (7) of Table 5. The non-using coefficients are close to zero with t values well below conventional levels of statistical significance. This implies that bond mutual fund performance and interest rate risk are only affected during periods of actual IRF engagement and not during periods where a user fund chooses not to employ IRF. Hence, it is the actual employment of IRF that drives bond funds' underperformance and increased exposure to the term factor.

Another possible concern may be that the results suffer from a possible endogenous relation between performance and IRF engagement. One possibility is that fund managers change their engagement behavior in response to past fund performance or risk in some form of tournament behavior (e.g., Brown *et al*, 1996; Schwarz, 2012). Therefore, in addition to the analysis in Table 3, which shows that past performance is not a significant determinant of complex investment engagement, all major analyses are carried out with lagged explanatory variables to mitigate endogeneity concerns.[28] To further alleviate any remaining concerns associated with endogeneity, the Endogeneity I Panel (c) of Table 6 includes past performance, measured by the 4-factor alpha for reporting period $t-1$ as an additional explanatory variable. Past performance has a positive impact on contemporaneous performance with a coefficient of 0.1283 (t value 2.72) implying performance persistence among bond funds when controlling for fund characteristics consistent with the findings by Huij and Derwall (2008). The coefficient on IRF engagement is -54 basis points with a t value of -4.04. This indicates that the possible endogenous relation between performance and IRF does not substantially influence the results. The Endogeneity II Panel (d) of Table 6 additionally includes past interest rate risk, measured by $\beta_{\text{TERM},i,t-1}$ from the 4-factor model, as funds may use derivatives in response to past risk exposures (Lynch-Koski and Pontiff, 1999). Past risk is negatively related to fund performance what partially explains the underperformance of bond funds. However, the results of a negative performance impact of IRF engagement still hold, with a coefficient of -58 basis points (t value -4.47). Regarding the findings of increased interest rate risk of bond funds employing IRF, results also remain qualitatively the same when including past risk and performance characteristics.

Performance and risk models

In our main analyses, we only use performance and risk measured with the 4-factor model defined in equation (1). However, in contrast to the literature on equity funds, where the Carhart (1997) 4-factor model is the workhorse model to assess performance, no standard model has emerged to measure bond fund performance. Hence, to mitigate concerns that the results are affected by performance model choice, we use further bond fund performance models based on multiple indices (e.g., Blake *et al*, 1993) and nested in the following equation:

$$\mathrm{er}_{i,d,t} = \alpha_{i,t}^{\mathrm{M}} + \sum_{k=1}^{K} \beta_{i,k,t}^{\mathrm{M}} \mathrm{er}_{k,d,t} + \varepsilon_{i,d,t} \quad (6)$$

Here, $\alpha_{i,t}^{\mathrm{M}}$ represents fund i's mean abnormal return measured with model M, while $\mathrm{er}_{k,d,t}$ is the daily excess return of bond index k on day t during reporting period t. Three specifications of equation (6) are employed. First, the Barclays US Aggregate Bond Index is used in a single-index model (SIM). The multi-index model 1 (MIM-1) includes the excess returns of the Barclays Capital US Corporate Investment Grade Index, the Barclays Capital US High Yield index, and the Barclays Capital US Aggregate Government index. To control for bond funds' possible equity exposure and to control for potential option-like features of bond fund returns, the second multi-index model (MIM-2) additionally contains US equity market excess returns measured by the value-weighted CRSP equity market index and a mortgage factor measured with the Barclays Capital US Mortgage Backed Securities index.

Furthermore, IRF use might alter risk and return profiles of bond funds and thus may lead to non-normal return distributions. Hence, standard performance measures may not be appropriate to examine abnormal returns of bond funds using IRF. Therefore, this paper also employs Leland's (1999) approach to control for higher moments in return distributions:

$$\alpha_{i,t}^{\mathrm{Lel}} = R_{i,d,t} - \beta_{\mathrm{agg},i,t}^{\mathrm{Lel}} \left[R_{\mathrm{agg},d,t} - r_{f,d,t} \right] - r_{f,d,t} \quad (7)$$

where $\beta_{\mathrm{agg},i,t}^{\mathrm{Lel}} = \frac{\mathrm{cov}\left[R_{i,d,t}, -\left(1+R_{\mathrm{agg},d,t}\right)^{-b}\right]}{\mathrm{cov}\left[R_{\mathrm{agg},d,t}, -\left(1+R_{\mathrm{agg},d,t}\right)^{-b}\right]}$ with $b = \frac{\ln\left[E\left(1+R_{\mathrm{agg},d,t}\right)\right] - \ln\left(1+r_{f,d,t}\right)}{\mathrm{var}\left[\ln\left(1+R_{\mathrm{agg},d,t}\right)\right]}$

Here, $\alpha_{i,t}^{\mathrm{Lel}}$ is Leland's alpha of fund i during semiannual reporting period t, $R_{i,d,t}$ is the daily return of fund i in semiannual reporting period t, $R_{\mathrm{agg},d,t}$ is the bond market return for day d measured with the Barclays US Aggregate Bond Index, and $r_{f,d,t}$ is the daily T-bill rate.

Results in Panel (a) of Table 7 show robust findings across all performance measures. The coefficient on the IRF dummy ranges from −143 basis points for Leland's alpha to −55 basis points for the MIM-2 alpha with t values all below −4.84 indicating significance at conventional levels. Thus, performance results are not driven by model choice. Panel (b) shows risk results for the respective models. Systematic exposure to bond price changes now does not solely encompass term risk, but also other risk drivers. Nevertheless, the betas exhibit strong correlations with IRF engagement as can be seen by the positive coefficients of the IRF dummy when explaining bond fund's single-index beta (0.1431) or Leland's beta (0.1488). Both coefficients are significantly different from zero with t values of 5.94 and 5.50, respectively. The aggregated beta factors from the MIM-1 and MIM-2 also capture bond price changes and are also positively related to the IRF dummy, with coefficients of 0.0883 and 0.0764. Consequently, IRF users increase bond mutual funds systematic exposure to changes in bond prices and interest rates.

Table 8 analyzes whether engagement in IRF also influences other risk characteristics. Fund return volatility is not affected indicating that higher exposure to interest rate risk increases the systematic part of bond funds' return variance and thus decreases idiosyncratic risk. While skewness is not

Table 7: Performance and term risk regression: different performance models

	Panel (a) Performance				*Panel (b) Risk*			
	SIM	*MIM-1*	*MIM-2*	*Leland*	*SIM*	*MIM-1*	*MIM-2*	*Leland*
IRF	−0.0125***	−0.0057***	−0.0055***	−0.0143***	0.1431***	0.0883***	0.0764***	0.1488***
	(−6.16)	(−4.84)	(−4.92)	(−5.69)	(5.94)	(4.72)	(4.03)	(5.50)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.36	0.28	0.31	0.28	0.29	0.27	0.22	0.24
N	15,252	15,252	15,252	15,251	15,252	15,252	15,252	15,251

Notes: This table shows results of a pooled panel regression of fund performance (Panel a) and risk (Panel b) on interest rate future engagement for different performance models. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. Performance is measured with raw gross fund excess returns, the single-index model (SIM), a multi-index model with a corporate bond, high yield, and government bond factor (MIM-1), the multi-index model 1 augmented with a mortgage bond the CRSP market factor (MIM-2), and Leland's (1997) alpha. Risk is measured with the slope on the aggregate bond index from the SIM model, the aggregated beta factors from the MIM-1 and MIM-2 model and Leland's beta. Performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. IRF is a dummy variable equaling one when a fund uses interest rate futures in the respective reporting period and zero otherwise. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. *t* values based on standard errors two-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

Table 8: Risk impact: other risk measures

	Volatility	*Skewness*	*Kurtosis*	*Default*	*Option*	*Equity*
IRF	−0.0000	0.0222	−0.2101**	−0.0453***	0.0474***	−0.0097***
	(−0.34)	(0.81)	(−2.22)	(−7.44)	(4.07)	(−4.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.30	0.21	0.07	0.38	0.26	0.12
N	15,252	15,252	15,252	15,252	15,252	15,252

Notes: This table shows results of a pooled panel regression of different fund risk measures on interest rate future engagement. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. Risk is measured with a fund's return volatility, skewness, kurtosis, and the slope on the default factor (Barclays Capital US High Yield Index and Barclays Capital US Intermediate Government Index), option factor (Barclays Capital Mortgage Index – Barclays Capital US Intermediate Government Index) and the market factor from the 4-factor model. Performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. Interest rate futures is a dummy variable equaling one when a fund uses interest rate futures and zero otherwise. ***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. *t* values based on standard errors two-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

affected by IRF engagement, kurtosis is lower for IRF users. The negative coefficient of −0.0453 (*t* value of −7.44) on the default factor also shows that IRF user funds focus less on spread strategies through picking high yield bonds. This indicates that bond mutual funds use IRF to increase their portfolio duration to profit from interest rate changes instead of picking individual bonds. However, the results document that this strategy does more harm than good as the performance of bond funds engaged in IRF suffers.

Propensity score matching analysis

To directly compare performance and risk of IRF users with nonusers, we employ a propensity score matching technique similar to Natter *et al* (2016) and Evans *et al* (2016). In a first step, we use a probit regression of IRF engagement on lagged fund characteristics to calculate a propensity score for each fund and each reporting period. In a second step, we match each reporting period in which a fund is engaged in IRF to its 20 nearest nonuser neighbor fund reporting periods.[29] Then performance and risk measured with the 4-factor model for the fund reporting periods with IRF engagement and for the control fund reporting periods are compared using paired mean comparison tests. Table 9 reports the results.

The gross performance difference between reporting periods in which user funds are engaged in IRF and the nonuser control reporting periods presented in Panel (a) is −48 basis points and significant at the 1% level. The difference in term risk is an economically meaningful 0.0662, also significant at conventional levels. In Panel (b), the probit regression for the calculation of the propensity score also includes past performance to control for possible endogeneity. The gross performance difference between IRF users and nonusers is still at −45 basis points, further supporting this paper's main results. In Panel (c), the inclusion of lagged interest rate risk in the probit regression also does not substantially alter the results. Funds employing IRF underperform their matched nonuser control funds by −43 basis points. This difference is significant at all conventional levels. Thus, our results could be attributed to the differential use of IRF.

Table 9: Performance and term risk: propensity score matching

	Performance	*Term beta*
Panel (a) All control variables		
Interest rate futures engaged	0.0013	0.6910
Control group	0.0061	0.6248
Difference	−0.0048***	0.0662***
Panel (b) All control variables plus performance		
Interest rate futures engaged	0.0013	0.6945
Control group	0.0058	0.6280
Difference	−0.0045***	0.0665***
Panel (c) All control variables plus performance and risk		
Interest rate futures engaged	0.0013	0.6945
Control group	0.0056	0.6805
Difference	−0.0043***	0.0140***

Notes: This table shows results of a matched comparison of fund performance and term risk between funds engaging in interest rate futures and an equally weighted non-using control group. Performance (term beta) is the intercept (slope on the TERM factor) from the 4-factor model. Performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. IRF is a dummy variable equaling one when a fund uses interest rate futures and zero otherwise. The equally weighted control group is constructed from the twenty nearest-neighbor fund reporting periods based on a propensity score matching. In Panel (a), matching is based on fund characteristics used in Table 5. In Panel (b), matching additionally uses a fund's lagged performance. In Panel (c), the matching additionally uses a fund's lagged risk. Statistical significance of the differences is based on two-sided, paired mean comparison tests. ***,**,* Significance at the 1, 5, and 10% level, respectively.

Controlling for restriction and engagement score

Fund engagement in IRF may be correlated with the use of other complex investments as indicated by the descriptive statistics on instrument use in Table 2. In this case, the negative performance impact ascribed to IRF may simply arise because of a fund's engagement in some other complex investment. Thus, to further isolate the effect of funds' employment of IRF on performance and risk, Table 10 controls for permissions and engagement in other complex investments. To do this, we calculate fund complex investment permission and engagement scores again as described in section "Complex investment permission and use", but this time without incorporating the IRF dummy.

Columns (1) and (2) in Panel (a) integrate a fund's complex investment permission score into equation (3). The relation between the permission score and fund performance is indistinguishable from zero, in line with the findings of Table 4. IRF engagement has a negative relation to fund performance, with coefficients of −63 and −29 basis points, both significant with t values of −4.96 and −2.00. When controlling for funds' actual engagement in complex investments in column (3) and (4), this negative relation between IRF and fund performance remains unaffected. Concerning fund exposure to the TERM factor, columns (5) and (6) of Panel (b) show that fund complex investment permission has no impact on risk over and above that of IRF. Including the engagement score in column (7) shows an increasing relation between term risk while being uncorrelated in column (8). However, the IRF coefficients remain positive. Overall, the results to this test confirm that IRF use is indeed an important factor in the determination of bond fund performance and risk.

Table 10: Performance and term risk regression: control for complex investment restriction and engagement score

	Panel (a) Performance				*Panel (b) Term beta*			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
IRF	−0.0063***	−0.0029**	−0.0065***	−0.0028**	0.0521***	0.0086	0.0409**	0.0100
	(−4.96)	(−2.00)	(−4.88)	(−2.00)	(2.97)	(1.09)	(2.31)	(1.26)
Permission	−0.0034	0.0042			−0.0697	−0.0207		
	(−1.05)	(0.84)			(−1.42)	(−0.83)		
Engagement			0.0036	−0.0028			0.1598***	−0.0169
			(1.17)	(−0.81)			(3.75)	(−0.86)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style-fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Fund-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R^2	0.46	0.49	0.46	0.49	0.21	0.77	0.21	0.77
N	15,252	15,252	15,252	15,252	15,252	15,252	15,252	15,252

Notes: This table shows results of a pooled panel regression of fund performance (Panel a) and term risk (Panel b) on interest rate future engagement controlling for a fund's complex investment restriction and engagement score. The sample consists of actively managed domestic bond funds with N-SAR filings and entries in the CRSP mutual fund database over the period 1999–2014. Performance (term beta) is the intercept (slope on the TERM factor) from the 4-factor model. Performance and risk are calculated for each fund and semiannual reporting period individually using daily gross excess fund returns. IRF is a dummy variable equaling one when a fund uses interest rate futures and zero otherwise. Restriction (engagement) is the weighted average score of all individual complex investment restriction (engagement) dummies excluding interest rate futures.
***,**,* Significance of the coefficient at the 1, 5, and 10% level, respectively. *t* values based on standard errors two-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

CONCLUSION

How bond mutual funds generate performance is of interest to investors and policy makers such as the SEC and therefore also to academic research. However, only few studies so far (e.g., Cici and Gibson, 2012; Huang and Wang, 2014) analyze bond fund investments, focusing on their bond holdings. We contribute to the literature on bond fund investments by showing that a substantial amount of bond mutual funds employ complex investments, such as derivatives, leverage, restricted securities, and income-generating strategies, while only few funds remain restricted from these activities. Moreover, complex instruments are more common among bond funds than among equity funds and lead to different effects than those reported for equity funds by various studies.

Being the first to analyze the use of complex instruments by bond funds, our novel results show no general relation between complex investment permission or use and performance. However, investing in interest rate futures, which is the case for almost half of the funds and in almost a third of all reporting periods, severely harms bond fund performance as IRF users significantly underperform nonusers. Moreover, our results show that IRF use significantly increases funds interest rate risk as users employ IRF for interest rate speculation by increasing their duration as opposed to hedging. While our study focuses on bond funds in the USA, our analysis is also applicable to other regions of the world. In this context, Frino *et al* (2009), Fong *et al* (2005) as well as Pinnuck (2004) examine derivatives use of equity mutual funds in Australia and similar studies are possible for bond funds. The European regulation on complex investments use is even more restrictive than in the USA so that the effects may be less pronounced; however, the also stricter reporting requirement should allow analyses also for European countries. That said, the freely available data on the derivatives use of US mutual funds present researchers with a great opportunity of further analyses.

Overall, our findings thus help answer the question what kinds of complex investments bond mutual funds use and to what effect. Hence, investors should be careful when investing in bond mutual funds and take into account these complex investments.

NOTES

1. See Table 4 of Investment Company Institute Fact Book (2016).
2. See http://www.sec.gov/news/pressrelease/2016-4.html (accessed: 01/28/2016).
3. N denotes the form category.
4. The repealing of the short–short rule with the Taxpayers Relief Act in August 1997 should represent a structural break in the use of derivatives by mutual funds that took place during this period. Thus, the period may not be comparable to the period from 1999 to 2014 used in this study during which the Act is in full effect.
5. For a detailed description of mutual fund complex investment regulation, see Chen *et al* (2013) and Rohleder *et al* (2017).
6. Another possible source would be the Morningstar Mutual Fund Database used by, e.g., Cici and Gibson (2012), as it encompasses information on all bond fund holdings. However, for equity funds Natter *et al* (2016) show that Morningstar holdings data underestimate the number of complex investment users compared to data from N-SAR filings due to window dressing and the reliance on string searching algorithms to identify complex investment positions.
7. Only Deli and Varma (2002) and Fulkerson *et al* (2014) analyze N-SAR filings for bond funds.
8. The results may be driven by differences between these fund types. Therefore, we include investment objective fixed effects in our regressions.
9. Furthermore, the short–short rule, which was repealed under the Taxpayer Relief Act of 1997, made it unattractive for mutual funds to engage in most complex investments prior to 1998.
10. Results are robust to changing the respective levels to 15 million in TNA and 24 monthly observations.
11. The EDGAR database is available at http://www.sec.gov/edgar.shtml.
12. The correlation for turnover ratios is lower as they are calculated for different periods in N-SAR and CRSP. Turnover is calculated per reporting period in N-SAR, while in CRSP it is calculated per calendar year.
13. One N-SAR filing may contain information on more than one individual fund.
14. Restricted securities are securities acquired in a private transaction from the issuer. Because there are rules that may limit funds to sell these securities, e.g., regarding the

holding period, an investment in restricted securities is illiquid. For details on restricted securities, see Rule 144 of the 1933 Securities Act.

15. In addition, Table 6 in section "Fees, using decisions and endogeneity" also reports results using net returns as a robustness check.
16. At least 36 daily observations are required for each semiannual reporting period.
17. Non-synchronous trading in daily returns may bias the results. Therefore, in unreported analyses, Dimson's (1979) approach with risk factors lagged and forwarded by one day is employed. The results, which are available upon request, are qualitatively the same.
18. Returns on the Barclays bond indices are taken from Thomson Reuters Datastream.
19. Equity market returns and T-bill rates are from Kenneth R. French's online data library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
20. If we use raw measures, the results stay the same.
21. In unreported results, portfolios are formed based on engagement scores in the highest and lowest third of all scores. Results remain the same.
22. According to unreported additional analyses, using lagged right-hand side variables does not affect the results.
23. In unreported additional analyses, we restrict the sample to funds with permission to use IRF to control for spurious results arising from potential differences between funds that voluntarily chose not to engage in IRF and those that are restricted from using IRF. Results are not affected by this specification.
24. Results, not reported for brevity, are also robust to the inclusion of family fixed effects.
25. For example, in the prospectus for the T. Rowe Price US Treasury funds, it states that "The fund may use derivatives to adjust its sensitivity to interest rate changes". For details, please refer to: http://individual.troweprice.com/public/Retail/Mutual-Funds/hProspectuses&Reports/Prospectuses-&-Reports.
26. Additionally, we use the slope coefficient from a four-factor regression where we specify the term factor in regression (3) as changes in the term spread, i.e. the 10-year treasury yield minus the 1-year treasury yield. Results, not reported for brevity, are robust to the use of this proxy.
27. As in Natter *et al* (2016), we define overall IRF users as of their first record of IRF use in the N-SAR filings. Thus, before first use, the NONUSER dummy is zero.
28. Results are available upon request.
29. We use 20 neighbor funds to eliminate idiosyncrasy. However, in unreported additional tests, we match using and nonuser reporting periods 1:1. The results are economically the same.

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APPENDIX: MERGING OF N-SAR AND CRSP

Table 11 displays averages of fund characteristics for both the merged N-SAR/CRSP sample (Panel a) and the complete actively managed domestic bond fund universe from CRSP (Panel b). Funds in the merged sample have higher TNA and are somewhat older. Evans *et al* (2016) and Rohleder *et al* (2017) find similar results for their matched samples of equity funds. Overall, there are no substantial differences between both datasets. Consequently, the sample is representative for the universe of all actively managed US domestic bond funds.

Table 11: Comparison of the merged N-SAR/CRSP and the complete CRSP active domestic bond fund samples

Year	*Panel (a) NSAR matched data*							*Panel (b) CRSP data*						
	Funds	*TNA ($ mil)*	*Expense ratio (% TNA, p.a.)*	*Turnover ratio (% TNA, p.a.)*	*Age*	*Implied net flow (% TNA)*	*Excess return*	*Funds*	*TNA ($ mil)*	*Expense ratio (% TNA, p.a.)*	*Turnover ratio (% TNA, p.a.)*	*Age*	*Implied net flow (% TNA)*	*Excess return*
1999	412	583	0.85	144.50	8.8	0.67	0.07	870	461	0.89	145.20	8.8	0.65	0.04
2000	456	449	0.85	148.90	9.1	−1.53	0.53	920	414	0.89	138.70	9.3	4.51	0.51
2001	470	439	0.87	156.50	9.6	2.92	0.52	927	463	0.89	150.90	9.7	4.33	0.52
2002	507	587	0.88	166.60	10.2	2.49	0.55	917	559	0.89	169.60	10.1	5.86	0.52
2003	526	702	0.88	159.00	10.6	2.42	0.67	920	682	0.89	166.10	10.5	3.77	0.62
2004	542	727	0.85	165.40	11.3	0.43	0.41	922	709	0.87	172.40	11.1	0.53	0.37
2005	669	894	0.84	149.40	11.9	0.12	0.21	926	742	0.86	153.40	11.4	3.69	0.18
2006	679	907	0.82	137.50	12.4	−1.09	0.41	895	805	0.83	144.40	12.2	0.70	0.42
2007	670	1039	0.80	145.20	12.8	3.22	0.39	881	911	0.81	147.30	12.6	2.21	0.38
2008	648	1113	0.78	152.20	13.6	0.85	−0.49	875	969	0.80	155.90	13.4	0.89	−0.58
2009	639	1281	0.77	156.10	14.3	2.68	1.24	848	1121	0.79	163.10	13.9	2.87	1.23
2010	628	1732	0.77	153.90	14.7	1.58	0.63	844	1501	0.79	159.60	14.3	2.11	0.63
2011	631	1891	0.76	153.00	14.9	1.61	0.38	861	1623	0.78	160.70	14.2	5.57	0.39
2012	671	2092	0.76	155.00	15.2	1.71	0.59	874	1815	0.77	159.50	14.2	12.70	0.59
2013	634	2136	0.76	139.80	15.5	0.53	0.05	884	1883	0.76	148.80	14.5	0.87	0.05
2014	466	1893	0.74	128.40	16.4	0.58	0.38	833	1961	0.74	136.80	15.7	0.70	0.28

Notes: This table compares average fund characteristics for two samples of active domestic bond funds during the period 1999–2014 by year. Panel a shows the relevant variables for funds with entries in both the N-SAR filings and the CRSP mutual fund database. Panel b shows the relevant variables for funds available in the CRSP mutual fund database. All variables are taken from the CRSP mutual fund database.