Essays on mutual funds, derivatives, and other complex instruments

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I. Introduction

Mutual funds are very important investment vehicles for investors saving for their retirement. This is reflected by USD 31.38 trillion total net assets managed by the worldwide mutual fund industry (Table 65 of Investment Company Institute Fact Book, 2015). Therefore, there exists a vast amount of research on whether mutual fund managers add value for their investors or not. Starting with Jensen (1968), research has analyzed how mutual funds perform compared to relevant benchmarks. Most of these studies find that the majority of mutual funds underperform (e.g., Gruber, 1996, Carhart, 1997, Fama and French, 2010). These studies mainly analyze mutual fund returns, but do not focus on how these returns are generated. How mutual funds invest, however, is a paramount question in order to understand the performance of mutual funds. Performance analyses based on mutual fund stock holdings, pioneered by Daniel et al. (1997), so far has mainly focused on equity mutual fund's domestic stock holdings (e.g., Chen et al., 2000; Pinnuck, 2003; Baker et al., 2010; Wei et al., 2014). Regarding other mutual fund types Cici and Gibson (2012) as well as Huang and Wang (2014) and Moneta (2015) analyze bond holdings of domestic bond funds while Hiraki et al. (2015) analyze international stock holdings of international funds.

However, next to investing directly into plain vanilla instruments such as stocks and bonds, mutual funds are also able to use derivatives, such as forwards, futures, and options, and other complex instruments, such as borrowing of money, short sales, and security lending. How these instruments are employed by mutual funds and how they may influence their performance and risk properties has not been studied extensively. While some studies exist with regards to how domestic equity funds use derivatives, they suffer from severe limitations due to their methodology (Cao et al., 2011) or data used (Lynch-Koski and Pontiff, 1999; Frino et al., 2009; Cici and Palacios, 2015). Or they do not consider performance and risk influence of actual derivatives use (Deli and Varma, 2002). Furthermore, no studies exist on how other mutual funds, such as bond and international equity funds use derivatives, with a notable exception being Adam and Guettler (2015), who investigate corporate bond funds employment of Credit Default Swaps.

Hence, the goal of this dissertation is to analyze the extent to which mutual funds employ derivatives and other complex instruments, such as borrowing of money, short selling, and security lending, and how this influences their performance and risk properties. To carry out this task, a unique dataset containing regulatory data on complex instruments use of mutual funds from the Securities and Exchange Commission (SEC) is employed. Chapter II investigates how equity mutual funds employ derivatives to mitigate the adverse effect of investor in- and outflows on mutual fund performance. Chapter III presents exhaustive evidence on how options are used by equity mutual funds and how this influences their performance and risk characteristics. Chapter IV provides evidence on the profitability of different index option strategies which may be employed by mutual funds. Chapter V analyzes how bond mutual fund use different complex instruments, such as derivatives, short sales, and repos and how these instruments alter their risk and performance characteristics. Chapter VI is concerned with how international mutual funds employ foreign currency derivatives to hedge against adverse currency movements. Finally, Chapter VII concludes and offers ideas for possible future research within this important literature segment. The remainder of this chapter briefly describes the main ideas and results of the articles making up this dissertation.

1.1. The role of derivatives in managing the adverse effects of investors flows on fund performance

The main goal of mutual funds is to attract investors to increase their assets under management, and consequently the fees they can obtain from their investor base (Berk and Green, 2004). The literature has shown that there is a positive relation between fund performance and ensuing investor flows (e.g., Sirri and Tufano, 1999). Investor flows, however, may also harm mutual fund performance as they force fund managers to deviate from their existing optimal portfolio or hold excessive, non-interest bearing cash (Edelen, 1999; Rakowski, 2010). In this dissertation's first paper, we use unique regulatory data on derivatives for 2,585 actively managed US equity mutual funds during the period 1998-2013, to contribute to this literature stream by analyzing how mutual funds use derivatives to manage the adverse effect of investor in- and outflows on performance. The results indicate that mutual funds overall suffer from flow risk as their performance is negatively related to investor flows. Nonusers of derivatives, such as equity options and futures, are affected more severely by flow risk, whereas derivatives users mitigate most of the negative impact of flows on their performance. This represents the costs associated with flow management. To control for the endogenous relation between performance and flow, we use a yearly cross-sectional Fama-MacBeth two-stage least squares (2SLS) instrument variable regression. The results hold for the individual derivatives and are most pronounced for heavy users of derivatives.

1.2. Equity funds' use of options and its effect on performance and risk characteristics

While the first article investigates how the cross-section of mutual funds differs with regard to the use of derivatives to manage the adverse effect of investor flows on fund performance, the second article analyzes how options use affects fund performance and risk directly using panel regressions. Research on equity funds option use has not found a clear relation between option use and fund performance or risk characteristics (e.g., Lynch-Koski and Pontiff, 1999; Cao et al., 2011; Cici and Palacios, 2015). In this article, we use a sample of 2,576 actively managed US domestic equity funds during the period 1998-2013 and find that option users have higher risk-adjusted performance than nonusers of about 67 basis points per year. Additionally, equity funds engage in options to decrease their systematic risk, measured by the market beta in a Carhart (1997) 4-factor model, by 7.76% (percentage points). We also show that funds on average use options to hedge and not to speculate as they mainly invest in protective puts and covered call strategies. These effects are only prevalent during periods of actual option engagement but not in times when funds choose not to use options. Furthermore, these findings are robust to a variety of robustness checks, such as controlling for endogeneity in the relation between options use and performance and risk, respectively and a 5-factor investable option strategy performance model to control for non-normal returns associated with option investments.

1.3. Performance and risk of equity index option strategies

To see how option strategies perform and consequently may influence the measurement of fund performance, the third article of this dissertation analyzes the performance and risk characteristics of a broad array of strategies based on equity index options. Existing research on option strategy performance varies in the strategies and the underlying equity indices under consideration. Moreover, the methodological approaches in many research papers do not take the unique properties of option strategy returns into account. As option payoffs are asymmetrical, option strategies' returns are often non-normally distributed (e.g., Leland, 1999) and therefore are not appropriate for analysis based on standard performance measures. Thus, in this paper, we compare the performance for a wide array of strategies, i.e. long and short call, put, straddle, strangle, butterfly, and put-spread as well as put-call-spread strategies for different strikes and maturities. We use real traded option bid- and ask-prices as well as performance measures that explicitly control for option strategies' non-normal return distributions, such as Leland's (1999) alpha and the Omega ratio (Keating and Shadwick, 2002). We find that for the period 2006-2010 writing options delivered large abnormal returns. Especially, shorting calls, puts, straddles, and strangles was profitable, indicating that researches and investors need to consider option strategy factors when assessing fund performance.

1.4. Bond funds' use of derivatives and other complex instruments and its effect on performance and risk characteristics

While this dissertation's first three articles are concerned with equity derivatives and their use by domestic equity funds, the fourth article analyzes bond funds' permission and actual employment of complex instruments, such as derivatives, borrowing of money, and short selling. Although bond mutual funds make up a large fraction of the whole mutual fund market, research mostly focuses on equity funds.[1] This lack of research is especially prevalent in research on how mutual funds invest. While there is a vast amount of research on equity fund holdings (e.g., Grinblatt and Titman, 1993; Daniel et al., 1997; Chen, 2000) and equity funds' use of complex investments, such as derivatives (Lynch-Koski and Pontiff, 1999; Almazan et al., 2004; Frino et al., 2009; Cao et al., 2011; Cici and Palacios, 2015), short selling (Chen et al., 2013), and security lending (Evans et al., 2015), analysis of how bond mutual funds invest is sparse.

The fourth paper of this dissertation is the first to use a comprehensive data set of regulatory information on complex investments from N-SAR filings for 1,059 bond mutual funds during the period 1999-2014.[2] We find that there is no overall relation between fund performance and risk characteristics and complex instruments. When looking at one of the most widely used complex instruments, interest rate futures employed by 45.8% of all sample funds, we show that users underperform their non-using peers by an economically substantial 51 basis points. This is grounded in bond funds using interest rate futures to increase their duration, i.e. to increase their interest rate risk.

[1] In the USA, e.g., bond funds have a market share of 18.26% TNA, whereas equity funds possess 39.33% of the market (Table 3 of Investment Company Factbook, 2015). In Germany the respective market shares are 21.62% for bond and 36.56% for equity funds (BVI Yearbook, p. 76),

[2] Only Deli and Varma (2002) analyze bond funds permission to use derivatives for the year 1997.

1.5. International funds' use of foreign exchange derivatives and its effect on performance and risk characteristics

The fifth article of this dissertation focuses on foreign currency derivatives (FCD). As domestic equity and bond funds, considered in the articles mentioned above, do not invest abroad, FCD are obviously not part of their investment universe. Hence, to analyze how FCD are used, I concentrate on international mutual funds. In contrast to the studies on mutual funds' complex instruments use mentioned above, regulatory data on FCD is not readily available from the SEC. Hence, in this paper I resort to scanning international equity funds' holdings data from Morningstar via string identification algorithms to classify FCD similar to Cici and Palacios (2015). For quarterly observations of 494 funds during the period 1999-2014, I find that funds heavily investing into FCD have lower exposure to the international equity market factor. This implies that international funds use FCD to hedge their foreign exchange rate risk rather than to speculate on currency movements. Risk-adjusted performance, however, is not affected by FCD.

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II. Article 1: Management of Flow Risk in Mutual Funds

Rohleder, M., Schulte, D., Wilkens, M.: Management of Flow Risk in Mutual Funds. *Review of Quantitative Finance & Accounting* forthcoming. (DOI: 10.1007/s11156-015-0541-1)

VHB: B, SJR: 0.544

III. Article 2: The Benefits of Option Use by Mutual Funds

Natter, M., Rohleder, M., Schulte, D., Wilkens, M. (2016): The Benefits of Option Use by Mutual Funds. *Journal of Financial Intermediation* 26, 142-168. (DOI: 10.1016/j.jfi.2016.01.002)

VHB: A, SJR: 1.7

IV. Article 3: The Performance of Equity Index Option Strategy Returns During the Financial Crisis

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Abstract. Equity index option writing strategies delivered abnormally high returns in the past. This empirical fact is often attributed to the so-called Path Peso argument, which states that put option prices reflect risk premiums for extreme jumps in prices and volatility, which are underrepresented in empirical data. We use option price data collected during the financial crisis as a natural experiment to examine whether the empirical evidence of abnormally high index option returns persists in periods with adverse outcomes of jump and volatility risk. To this end, we use S&P 500, DAX, and EURO STOXX 50 option price data to analyze returns of a wide array of index option strategies and find that writing options remained profitable during the adverse conditions of the period 2006-2010.

JEL Classification: G11, G12, G19

Keywords: Option strategies, index options, performance measurement

1. Introduction

This is the first study to compare the performance of different index option strategies across different underlyings using the financial crisis as a natural experiment for jump and volatility risk. This is relevant as many institutional investors such as hedge funds as well as pension and mutual funds use index option strategies to try to increase their overall performance. Using actual bid-ask option prices and controlling for non-normality of index option returns, this paper shows performance results for index option strategies across different maturities and strikes for the S&P 500, DAX, and EURO STOXX 50 during the period around the 2008 financial crisis.

Writing equity index options has been profitable in the past.[1] Merton, Scholes, and Gladstein (1978), Zivney and Alderson (1986), Whaley (2002), Hill et al. (2006), and Feldman and Roy (2005) find covered call strategies on different S&P indices to be profitable over periods ranging from 1963 to 2005.[2] Ungar and Moran (2009) find that a put write strategy on the S&P 500 strategy outperforms its underlying index as a benchmark. Schneeweis and Spurgin (2000) find that option-based indices incorporating short calls, long puts, short collars, short straddles, and short strangles have an enhanced risk-return profile in comparison to the S&P 500. Santa-Clara and Saretto (2009) consider a wide range of options and specifications and present one of the few papers incorporating transaction costs into their considerations. They find transaction costs lead to underperformance of otherwise outperforming option strategies on the S&P 500. Jarnecic (2004) as well as Frino and Wearin (2004) show that the covered call strategy is optimal for the Australian ASX 200 index. Isakov and Morard (2001) find outperformance for writing out-of-the-money (OTM) calls in

[1] Table A1 in the Appendix aggregates the results of the empirical literature.

[2] A covered call equals a long position in an index and a short call on the same index.

the Swiss market. For the FTSE 100, Fernandes and Machado-Santos (2002) find that covered calls are optimal compared to protective puts.[3] Kapadia and Szado (2007) show that one-month 2% OTM calls on the Russell 2000 are optimal. Behr, Graf, and Güttler (2008) find that selling one-month 5% OTM calls is a superior investment to other option strategies with the DAX as an underlying. However, many of these studies do not adequately control for the non-normality of option strategy returns making these results unreliable.

The profitability of index option strategies is often attributed to the Path Peso argument that option prices reflect risk premia for extreme jumps in prices and volatility, which are underrepresented in empirical data. Another explanation for the profitability of option writing strategies is the perception that options are too expensive. This statement is closely connected to the fact that the Black-Scholes implied volatility is systematically higher than realized volatility. One argument supporting this explanation, stated for example by Bollen and Whaley (2009), is that demand for options exceeds their supply. This is because only few players, such as investment banks or hedge funds are willing to sell options, while most institutional and retail investors are option buyers. A second argument is that heterogeneous expectations regarding the option payoff lead to option overpricing. Protection buyers may be more concerned with downside risk and therefore pay more than fair value for an option.

Another line of research argues that no mispricing prevails in option markets once additional risk factors are considered. Coval and Shumway (2001) show that there is a risk premium for systematic stochastic volatility in option returns. Broadie et al. (2009) support this line in the literature and state that risk premia for jump risk, peso problems, and stochastic volatility can explain the option-pricing anomaly. Driessen et al. (2009) argue that the relative

[3] A protective put is long in an index and long in a put option on the same index.

expensiveness of index options compared to options on single stocks is due to a correlation risk premium. However, they also consider inefficiencies in index option markets as a reason for overpriced index options. They find that, in the spirit of Shleifer and Vishny (1997), it is not possible to arbitrage overpricing away due to transaction costs. Similarly, in an empirical study using a variety of models, Jones (2006) finds no sufficient explanation for abnormal returns when selling S&P 500 index options.

This paper uses the financial crisis to examine whether the empirical evidence of abnormally high index option returns persists in periods with adverse outcomes of jump and volatility risk. Hence, the Path Peso argument that rare events are underrepresented in empirical data is not valid in this study. The results in this paper show that risk premiums have been high enough to compensate for the extreme volatility.[4] Thus, this paper contributes to the existing literature on index option strategies in several ways. First, it assesses the performance of a wide array of index option strategies for various maturities and strike levels for a common dataset comprised of actually traded option prices for the S&P 500, DAX, and EURO STOXX 50. Thus, it consolidates the fragmented literature on option-based strategies. To investigate the profitability of trading the volatility premium, this paper analyzes long and short calls, puts, straddles, strangles, and butterflies.[5] To gather information regarding the performance of implied skew trading strategies, put spreads, and put-call spreads are analyzed. Second, in contrast to many studies, e.g., Zivney and Alderson (1986), Schneeweis and Spurgin (2000), Whaley (2002), and Hill et al. (2006), non-normal returns of index option strategies are controlled for by applying performance measures that consider higher moments of index option return distributions. This is necessary since option returns are asymmetric and

[4] During the period under investigation, S&P 500 40-day volatility rises to levels exceeding those in 1987 and reaching levels only seen before in 1929.

[5] For a detailed description of these strategies see Section 2.

often exhibit high (positive or negative) skewness and excess kurtosis. Therefore, existing studies may be misleading. Third, the methodology incorporates bid-ask transaction costs to show how much investors are able to earn with these strategies in the real world. Fourth, due to transaction costs both long and short strategies on the same option are analyzed, as in markets with friction they are not mere mirror images to each other.

The structure of the paper is as follows. Section 2 presents the definition of index option strategies while section 3 presents the data set. Section 4 discusses the empirical performance of index option strategies. Section 5 concludes.

2. Definition of Index Option Strategies

This paper focuses on the short and long leg of seven index option strategies. To assess the notion that a high volatility premium in comparison to its empirical counterpart leads to profitable option strategies, strategies that trade this volatility premium are analyzed. In addition to basic call and put strategies, these are straddles, strangles, and butterflies. Long straddles involve the purchase of a call and a put with the same maturity and strike. Long strangles are similar to straddles, however the strike of the call is higher than the one of the put. Thus, these strategies depend mainly on the development of implied market volatility. A long butterfly strategy is constructed by buying one in-the-money (ITM) as well as one OTM call and selling two at-the-money (ATM) calls, all with the same maturity. Therefore, long investors profit in low volatility environments whereas short investors profit when volatility is high.

To profit from the potential overpricing of OTM put options, investors may trade the implied skew, i.e. the difference in implied volatility between OTM and ITM options. This may be achieved by investing in put spreads and put call spreads. A long put spread combines a short position in an OTM put with a long position in an ATM put. In a long put call spread, the ATM put is substituted by an ATM call. For the corresponding short strategies, the long components are short and vice versa. Table 1 gives an overview of the strategies analyzed in this paper.

[Insert Table 1 about here]

Because bid and ask prices are employed, long positions are not merely the mirror image of short positions. Consequently, both long and short strategies for maturities of one month, two months, and three months are considered. Call, put, and straddle strategies with six strikes, namely 90%, 95%, 100%, 102%, 105%, and 110% of the underlying's price are studied. The more complex strategies are investigated for two strikes each. Strangles are analyzed for put and call options with strikes 5% and 10% OTM, respectively. For butterflies, ITM and OTM calls at the ATM strike plus and minus 5% and 10%, respectively, are examined. For put spreads (put call spreads) the ATM call (put) stays ATM while the short put is 5% and 10% OTM, respectively. Each strategy is analyzed in combination with an investment in the underlying index. Hence, the return *r* of option strategy *i* is given by the following equation:

$$r_{k,i,t} = \frac{index_{k,t} + opt_{i,t}}{index_{k,t-1} + opt_{i,t-1}} - 1. \qquad (1)$$

Here, $index_{k,t}$ is the value of the underlying index *k* and $opt_{i,t}$ is the value of the option(s) belonging to strategy *i* at time *t*. Interest from the investment of the proceeds of option sales is not considered. Each option is rolled after one month, regardless of its maturity, e.g., a one-month option is held until the last trading day before expiry, and a three months option until it has a maturity of two months. For short positions, the respective option is sold in *t* and bought back in *t*+1.

3. Data

The dataset used in this study is based on end-of-month bid and ask prices for calls and puts as quoted on Bloomberg. If for a certain combination of underlying, strike, and maturity no option price is available, the missing data is filled by computing a proxy option price based on the implicit bid-ask volatility of the available option with the most adjacent strike. The period of analysis is between January 2006 and September 2010 for options on three of the world's most important equity indices: The S&P 500, EURO STOXX 50, and the DAX.[6] Table 2 shows the descriptive characteristics of these underlyings. A remarkable feature of the period under investigation is the downturn in all indices during the financial crisis of 2008. This period is of special interest for research on index option strategies since it represents a rare event, which might significantly affect the performance of option-based strategies. The results can be interpreted as a real-life stress test as they involve extreme realizations of jump risk and stochastic volatility, two risk factors that have been argued to explain the assumed mispricing of option.

[Insert Table 2 about here]

Figure 1 shows the realized volatility of S&P 500 returns since 1928. This represents more than 80 years of data and shows that volatility levels of 80% as reached in 2008 are extremely rare. Only at the start of the Great Depression in 1929, the stock market crash led to a volatility of comparable magnitude. The level of 70% was only reached in 1929, 1987, and 2008. Notably, the burst of the dot-com bubble in 2000 resulted in volatilities of only 40%. Hence, the experience during the course of the financial crisis represents an extremely rare event to evaluate index option strategy performance since these strategies offer a premium for bearing such rare event risk.

[6] Liquid option prices for other indices are sparse and therefore not considered in this study.

[Insert Figure 1 about here]

Figure 1 also shows that the number of severe market downturns or jumps, i.e. returns smaller than the 0.5% quantile of daily returns (-4.47%), has been high for an extended period during the financial crisis in 2008. Only during the Great Depression severe market downturns were of a higher frequency. Hence, the financial crisis of 2008 acts as natural experiment for extremely adverse market conditions making the Path Peso argument, that rare events are underrepresented in empirical data, invalid for our study.

[Insert Table 3 about here]

Our empirical analysis is based on bid and ask prices, Table 3 shows a descriptive analysis of bid-ask spreads for the different option specifications. Bid-ask spreads are calculated as the difference of bid and ask price in month *t*, when buying (selling) the option, plus the difference of bid and ask price in month *t*+1, when selling (buying) the option. The bid-ask spread is scaled by the option bid-price to make it comparable for different option specifications. Overall, the average bid-ask spread is 3.1%. Given the average size of the spread, it is obvious that it should be taken into account when assessing the performance of index option strategies. Bid ask spreads are lowest for S&P 500 options indicating a liquid market. EURO STOXX 50 and DAX options show slightly higher spreads implying less liquid markets. Furthermore, bid-ask spreads are higher the higher the option is OTM as can be seen in Figure 2.

[Insert Figure 2 about here]

4. Performance analysis

4.1. Overview of Risk and Return Statistics

Table 4 reports risk and return characteristics for a wide array of index option strategies on the S&P 500, DAX, and EURO STOXX 50, respectively. As expected, most of the strategies have non-normal return distributions since they have significant skewness and excess kurtosis. Long option strategies in most cases cannot enhance index returns as the option premia and the bid-ask spreads paid are larger than option payoffs. Only long OTM put strategies on the S&P 500 are superior to the stand-alone index return. The severe downturn of the underlying indices in the sample period has led to some huge payoffs for long put investors. For the DAX, long put call spreads with two and three months maturity increase index returns.

[Insert Table 4 about here]

Shorting options, although not a mere mirror image of the long strategies in most cases enhances index returns on average. Only the short butterfly strategy decreases return across all underlyings. For the DAX put spreads and put call spreads also do not enhance returns with their short legs. Thus, it seems that writing options is profitable at first glance. When trading volatility in a non-directional way with straddles and strangles, the short leg of these strategies have positive returns and for the long leg the returns become negative. Strategies involving trades of more than one options suffer from bid-ask spreads and hence offer low returns. In terms of the hit ratio, short near-the-money call strategies perform best for all indices.[7] In up to 74% of all observations they lead to a profit.

[7] The hit ratio is calculated as the fraction of the number of months with positive returns to the total number of months.

4.2. *Risk-Adjusted Performance using the Omega Ratio*

To account for non-normality of option strategy return distributions, performance is measured with the Omega ratio as introduced by Keating and Shadwick (2002):[8]

$$\Omega_i = \frac{\int_x^b [1-F(r_i)]dr}{\int_L^x F(r_i)dr}. \tag{2}$$

Here, the nominator is one minus the cumulative distribution function exceeding the threshold *x*. The denominator is the cumulative distribution function for returns up to the threshold *x*. Here, this threshold is set equal to zero. The Omega ratio thus represents the ratio of probability weighted positive returns to probability weighted negative returns. Hence, this measure contains all available information concerning the distribution of index option strategy returns.

Table 5 shows Omega ratios for the index option strategies. For the S&P 500 nearly all short option strategies have Omega ratios exceeding the stand-alone index's Omega ratio of 0.9896 implying outperformance of the option strategies. The best performing strategies are trading the volatility premium despite the adverse environment of the 2008 financial crisis. Specifically, writing straddles has the highest Omega ratio for all indices. For the S&P 500 and EURO STOXX 50 straddles with a maturity of two months and strikes of put and call at 90% of the underlying have the largest Omega ratio. Existing studies have found 5% OTM calls on the S&P 500 to be optimal.[9] However, most of these studies suffer from at least one of the shortcomings discussed in the introduction. For the DAX as the underlying the highest Omega Ratio is achieved by writing two months straddles. This straddle consists of a call 5% OTM and a put 5% ITM. The three strategies mentioned all exceed the Omega ratios of the

[8] Additionally, Sharpe and Sortino Ratios are calculated for all strategies. Since the results do not differ substantially, they are not reported in this paper.

[9] See Table A1.

underlying indices alone while having positive mean returns with relative low volatility as can be seen in Table 4. The straddle strategy on the DAX has the highest yearly average return with nearly 21.6% p.a., but it also has the highest monthly standard deviation with 7.7%. The strategies with the highest Omega ratio for EURO STOXX 50 and S&P 500 offer lower returns, but also very low standard deviations.

[Insert Table 5 about here]

Most of the other specifications with short exposure to the implied volatility premium also yield positive performance according to the Omega ratio. Only for the EURO STOXX 50 enhancing index returns with some short option strategies lead to worse Omega ratios than a stand-alone investment in the index. Regarding options on the DAX and the S&P 500, writing calls delivers positive Omega ratios even when considering transaction costs. This is in line with the existing literature as summarized in Table A1. Shorting puts, strangles and straddles is also rewarding, yielding Omega ratios above the Omega ratio of an investment in the index alone (1.206).

For most specifications, the butterfly strategy is unprofitable. This may be caused by transaction costs since this strategy involves the sale and purchase of at least four options every month. Especially the bid ask spread of OTM options is substantial. The strategies trading the implied skew also do not offer high Omega ratios. Only the short put spread enhances index returns across indices and maturities.

4.3. *Factor Risk-Adjusted Performance using Leland's Alpha*

The results so far offer insights into which option strategy had the highest reward to risk ratio during the period from 2006 to 2010 according to an analysis of all return distribution moments via the Omega ratio. However, performance assessment with the Omega ratio has some drawbacks. First, it is dependent on the arbitrarily chosen threshold *x*, which may differ among investors. Second, it does not consider a benchmark. Hence, to examine if option index strategy returns could be achieved with a (levered) direct index investment, this section presents results for a benchmark-adjusted performance measure. Nonlinearity and asymmetry in index option strategies may bias standard CAPM-based performance measures such as Jensen's alpha. Leland (1999) shows that long (short) option positions generate positive (negative) skewness leading to negatively (positively) biased alphas. Table 4 clearly shows that index option strategy returns are asymmetrical. Hence, to control for these higher moments in index option strategy returns, Leland's (1999) performance model is employed:

$$\alpha_{i,Leland} = E(r_i) - \beta_{i,Leland}[E(r_{Mkt}) - r_f] - r_f, \tag{3}$$

$$\text{where: } \beta_{i,Leland} = \frac{cov[r_i, (1 + r_{Mkt})^{-b}]}{cov[\mathrm{r}_{\mathrm{Mkt}}, (1 + r_{Mkt})^{-b}]}$$

$$\text{with } b = \frac{ln[\mathrm{E}(1 + r_{Mkt})] \quad ln(1 + r_f)}{var[ln(1 + r_{Mkt})]}$$

Here, $E(r_i)$ is the return of strategy *i*, and $E(r_{Mkt})$ is the underlying index return.[10] Table 6 shows Leland's alpha for each strategy. Since p-values to assess the significance of Leland's alpha are not readily available, they are bootstrapped using 1,000 bootstrap repetitions of the index option strategy returns.

[Insert Table 6 about here]

The majority of long index option strategies have negative alphas, although mostly insignificantly so. Only strategies long in the index and a straddle significantly underperform the stand-alone index. Somewhat surprisingly, protecting the index with a long put did not add value during the period of study incorporating the financial crisis of 2008. This implies that protective put strategies are not worth more than the option premium paid. This indicates

[10] Index return data is from Datastream.

that after transaction costs long index option strategies do not add value once systematic market risk is considered.

The short legs of index option strategies offer mixed results. Short butterfly strategies underperform across all specifications, sometimes even significantly so. Augmenting index return with trades of the implied skew leads to both positive and negative Leland alphas depending on the specification. The majority of alphas, however, are statistically indistinguishable from zero for these strategies.

Most short call, put, straddle and strangle strategies offer positive alphas, although generally insignificant ones for the S&P 500 and EURO STOXX 50 as the underlying index. Only 2 months short straddles with strikes at 102% and 105% of the underlying lead to positive and significant alphas for the S&P 500. No index option strategy leads to significant outperformance for the EURO STOXX 50. The DAX offers significant positive Leland alphas for most of these strategies' specifications implying improved risk-adjusted returns when augmenting the DAX with basic short option strategies.

For the S&P 500, the strategy with the highest Omega ratio offers no benchmark adjusted profits. Its Leland's alpha is positive with 0.0052 but with a p-value of 0.13 it is indistinguishable from zero. However, short straddle strategies with maturities of two months and calls (puts) 2% and 5% OTM (ITM) deliver positive Leland's alphas up to 9.84% per annum as well as good Omega ratios. The best index option strategy for the DAX according to the Omega ratio, a two months 5% OTM straddle, also adds value according to its Leland's alpha of 0.0128 with a p-value of 0.00. This implies that a short straddle strategy on the DAX enhances its returns and leads to a yearly risk-adjusted outperformance of nearly 15.36%. For the EURO STOXX 50, the strategies with the highest Omega ratio, writing 2 months and 3 months straddles, have positive and significant alphas, ranging from 0.0023 to 0.0068 per month, but all insignificantly so. Writing calls and puts on the DAX, also leads to positive performance according to Leland’s alpha. The yearly outperformance with these covered Call and short put strategies range from 0.70% to 10.44%. Overall, shorting the volatility premium via short straddles adds value for the DAX regardless of the performance measure employed.

5. Conclusion

This study presents the performance and risk profile of a comprehensive set of option-based strategies, such as long and short calls, puts, straddles, strangles, and butterfly strategies. All strategies are investigated for the S&P 500, DAX, and EURO STOXX 50, various maturities, and various option strikes. We deliver new evidence on their performance by taking into account the realized volatility risk and jump risk in the recent financial crisis during which realized volatility of the S&P 500 surpassed the levels seen in 1987 and reached the highs seen only in the Great Depression 1929. To compute strategy returns after transaction costs, we use a dataset comprising bid and ask option prices. By doing this, our study consolidates existing studies, which mostly focus on single option strategies and single indices.

We find that most option-writing strategies capturing the volatility risk and jump risk premium such as shorting OTM calls, puts, straddles or strangles, deliver high abnormal long run returns even when including the period 2008-2010 indicating that realized volatility premiums have been high enough to stay profitable after such a market turmoil. Furthermore, risk-adjusted performance measures such as the Omega Ratio and Leland’s alpha still show high risk-adjusted returns. Butterfly strategies forego a large part of the premium by hedging the tails with a long position in out-of-the money options.

Further research could be carried out to investigate the performance of option-based strategies for other asset classes such as bond futures, currencies, as well as commodities futures in order to assess whether the volatility risk premiums are as high as in the equity market.

Appendix

Table A1 Empirically tested index option strategies

This table reports empirically tested strategies for index options on the S&P 500 (SPX), DAX 30 (DAX), ASX 100 (ASX), FTSE 100 (FTSE), and Russell 2000 (RUT) based on the existing literature. Bold marks an option specification, which was found to be optimal by at least one study. Results are based on findings in Feldman and Roy (2005), Hill et al. (2006), Santa-Clara and Saretto (2006), Schneeweis and Spurgin (2000), Ungar and Moran (2009), Behr, Graf, and Güttler (2008), Fernandes and Machado-Santos (2002), Kapadia and Szado (2007), Jarnecic (2004), and Frino and Wearin (2004).

	95%	98%	100%	101%	102%	103%	105%	107%	110%
Panel A: Covered call									
1 day			**SPX**	SPX					
1 month	RUT	RUT	SPX, DAX, RUT	**SPX,** DAX	**SPX, RUT**	DAX	**SPX, DAX,** RUT		
45 days			SPX				**SPX**		SPX
2 months	RUT	RUT	SPX, RUT		RUT		SPX, RUT	SPX	
3 months	FTSE		SPX, DAX, FTSE	SPX, DAX, ASX		DAX	SPX, DAX, **FTSE**		SPX
6 months									
Panel B: Protective put									
1 day			SPX	**SPX**					
1 month			SPX						
45 days	**SPX**		SPX						
2 months									
3 months	FTSE		FTSE				FTSE		
6 months	SPX		SPX						
Panel C: Short straddle									
1 day			**SPX**			SPX			
1 month			**SPX**			SPX			
45 days			SPX						
2 months									
3 months									
6 months			SPX						
Panel D: Short strangle									
1 day									
1 month									
45 days						SPX		SPX	
2 months									
3 months						SPX		SPX	
6 months									

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Figures and Tables

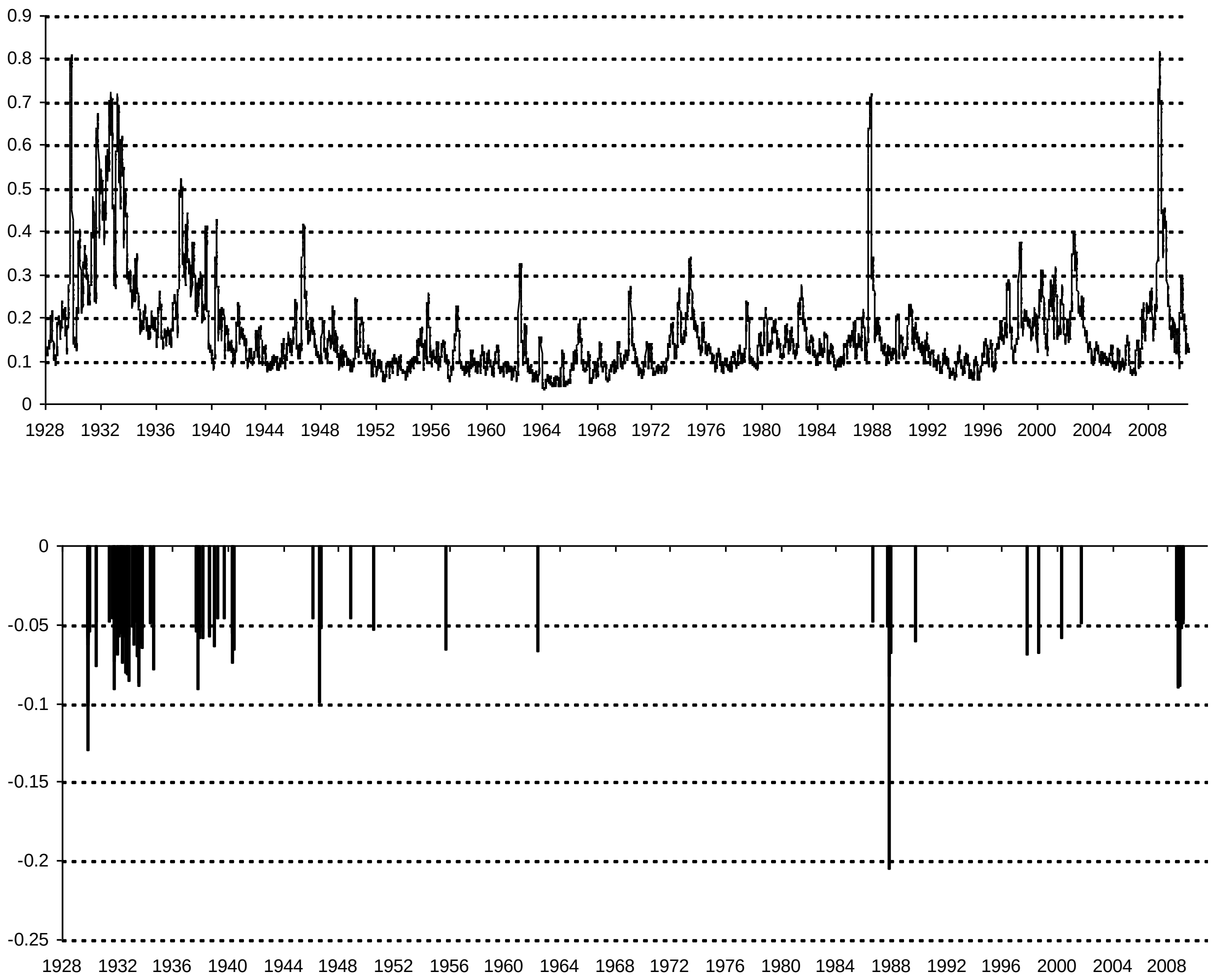

Figure 1 Upper chart: realized 40 day volatility of S&P 500 Index returns from February 1928 to September 2010. Lower chart: daily returns smaller than -3.44% which represents the 0.5% quantile of daily returns over the whole period.

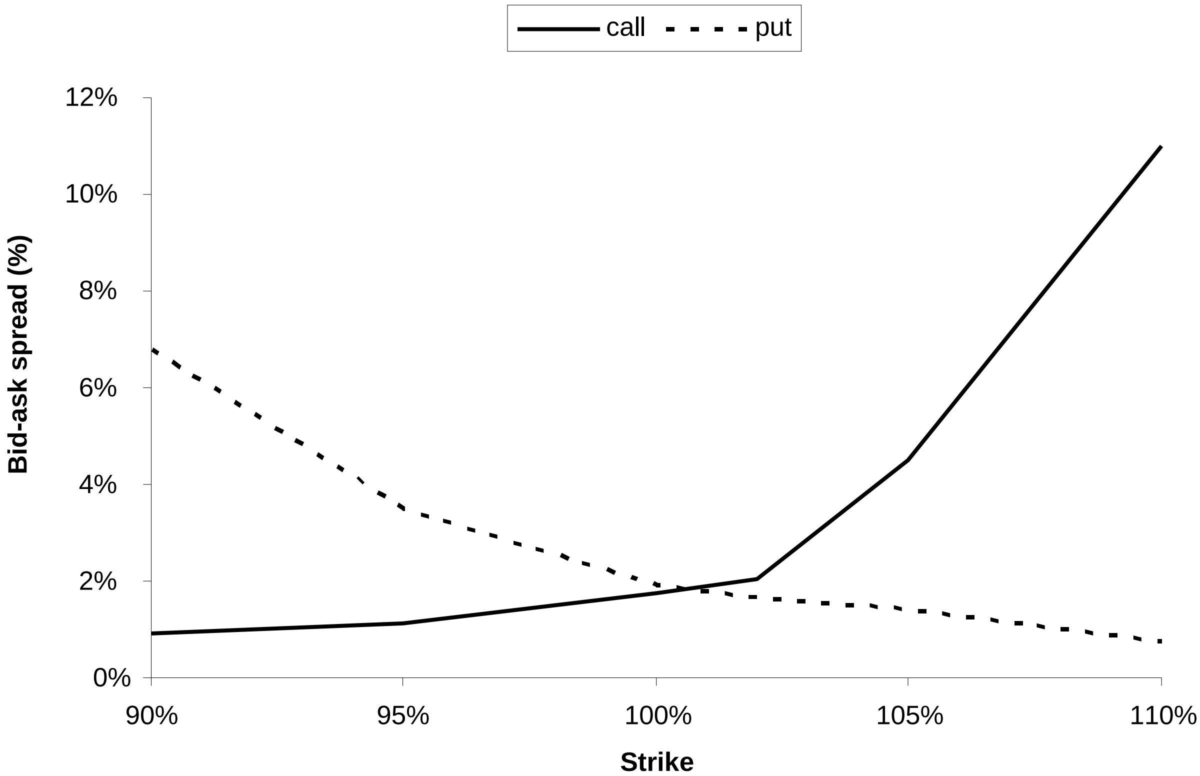

Figure 2 Average bid-ask spreads of calls and puts. This figure shows the average bid-ask spreads of calls and put depending on their strike level.

Table 1 Construction of index option strategies

This table depicts the construction of long option strategies. For the short strategies, the signs are inverted. Each option is presented as a function *f*(*m*, *s*) of its maturity *m* and strike *s*. For example, a one month 5% out-of-the-money call is denoted by call(1M, 105%). Options that make up complex strategies have their strikes denoted as distance from the at-the-money strike (ATM).

Strategy	Description	Maturities *m*	Strikes *s*
Call	Call(*m*, *s*)	1M, 2M, 3M	90%, 95%, 100%, 102%, 105%, 110%
Put	Put(*m*, *s*)	1M, 2M, 3M	90%, 95%, 100%, 102%, 105%, 110%
Straddle	Call(*m*, *s*) + put(m, s)	1M, 2M, 3M	90%, 95%, 100%, 102%, 105%, 110%
Strangle	Call(*m*, atm, - *s*) + call(*m*, atm, + *s*)	1M, 2M, 3M	5%, 10%
Butterfly	Call(*m*, atm, - *s*) - 2*call(*m*, atm, + *s*) + call(*m*, atm + *s*)	1M, 2M, 3M	5%, 10%
Put spread	-Put(*m*, atm, - *s*) + put(*m*, atm)	1M, 2M, 3M	5%, 10%
Put call spread	-Put(*m*, atm, - *s*) + call(*m*, atm)	1M, 2M, 3M	5%, 10%

Table 2 Descriptive statistics of index data

This table reports descriptive statistics for underlying indices of index option strategy. Mean positive (negative) return is the average of all monthly returns > 0 (<0), monthly maximum loss is defined as the minimum monthly return over the entire period. Maximum drawdown is the maximal historic percentage loss in value from peak to trough. Hit ratio is the ratio of positive returns to total returns of a strategy. Omega ratio is computed as follows $\Omega_i = \left(\int_x^b [1 - F(r_i)]dr\right) / \left(\int_L^x F(r_i)dr\right)$,where the nominator is one minus the cumulative distribution function exceeding the threshold x. The denominator is the cumulative distribution function for returns up to the threshold x. Here, this threshold is equal to 0. The period covered is from January 2006 to September 2010.

	S&P 500	DAX	EURO STOXX 50
Mean return	-0.0002	0.0042	-0.0030
Mean positive return	0.0293	0.0407	0.0367
Mean negative return	-0.0535	-0.0501	-0.0476
Maximum monthly loss	-0.1694	-0.1507	-0.1469
Volatility	0.0519	0.0592	0.0563
Skewness	-0.7665	-0.4199	-0.4205
Kurtosis	3.8590	3.8907	3.6236
Omega ratio	0.9896	1.2096	0.8655

Table 3 Bid-ask spreads

This table reports average monthly bid-ask spreads for different underlying indices, separated into calls and puts with one month, two months and three months maturity. Bid-ask spreads are calculated as the difference of bid and ask price in *t*, when buying (selling) the option, plus the difference of bid and ask price in *t*+1, when selling (buying) the option scaled by the respective mid option price. The period covered is from January 2006 to September 2010.

	S&P 500						DAX						EURO STOXX 50					
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%
Panel A: Call																		
1 month	0.007	0.012	0.020	0.030	0.056	0.134	0.027	0.024	0.041	0.047	0.110	0.200	0.011	0.014	0.044	0.040	0.089	0.157
2 months	0.001	0.002	0.007	0.010	0.028	0.079	0.011	0.022	0.013	0.015	0.031	0.104	0.005	0.015	0.013	0.021	0.033	0.104
3 months	0.001	0.001	0.003	0.005	0.009	0.044	0.007	0.007	0.006	0.007	0.033	0.098	0.014	0.005	0.010	0.010	0.015	0.071
Panel B: Put																		
1 month	0.079	0.065	0.038	0.029	0.012	0.005	0.140	0.087	0.043	0.042	0.030	0.018	0.140	0.087	0.043	0.043	0.031	0.018
2 months	0.027	0.012	0.005	0.004	0.002	0.001	0.058	0.019	0.012	0.009	0.020	0.007	0.058	0.019	0.001	0.009	0.096	0.007
3 months	0.009	0.004	0.003	0.002	0.002	0.001	0.005	0.012	0.008	0.006	0.006	0.006	0.050	0.012	0.009	0.006	0.006	0.006

Table 4 Overview of Risk and Return Statistics

This Table reports descriptive statistics for option strategy returns based on Bloomberg end-of-month bid-ask prices. Panel A shows the results for options on the S&P 500, Panel B for options on the DAX, and Panel C for options on the EURO STOXX 50. Mean positive (negative) return is the per annum average of all monthly returns > 0 (<0), the monthly maximum loss is defined as the minimum monthly return over the entire period. Hit ratio is the ratio of periods with positive returns to total periods. The covered period is from January 2006 to September 2010.

	short call						long call						short put						long put					
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%
													Panel A: S&P 500											
Maturity 1M																								
Avg. return	-0.0011	-0.0017	-0.0014	0.0003	0.0012	0.0006	-0.0020	-0.0011	-0.0008	-0.0020	-0.0021	-0.0011	-0.0005	-0.0006	0.0005	0.0024	0.0027	0.0012	0.0003	0.0008	0.0003	-0.0014	-0.0021	-0.0005
Avg. pos. return	0.0142	0.0165	0.0217	0.0240	0.0292	0.0298	0.0519	0.0514	0.0460	0.0363	0.0319	0.0303	0.0316	0.0340	0.0442	0.0534	0.0558	0.0563	0.0289	0.0277	0.0189	0.0184	0.0170	0.0142
Avg. neg. return	-0.0271	-0.0286	-0.0445	-0.0512	-0.0483	-0.0524	-0.0699	-0.0673	-0.0524	-0.0550	-0.0520	-0.0500	-0.0584	-0.0675	-0.0776	-0.0702	-0.0737	-0.0732	-0.0444	-0.0383	-0.0293	-0.0286	-0.0240	-0.0205
Max. loss	-0.0665	-0.0984	-0.1269	-0.1485	-0.1485	-0.1672	-0.2493	-0.2253	-0.2037	-0.1868	-0.1868	-0.1714	-0.2366	-0.2580	-0.2734	-0.2815	-0.2815	-0.2775	-0.1212	-0.1121	-0.0814	-0.0814	-0.0808	-0.0730
Volatility	0.0261	0.0290	0.0388	0.0425	0.0472	0.0516	0.0835	0.0789	0.0671	0.0621	0.0564	0.0523	0.0595	0.0668	0.0789	0.0832	0.0874	0.0879	0.0466	0.0420	0.0328	0.0335	0.0301	0.0272
Skewness	-0.69	-1.07	-1.02	-1.08	-0.78	-0.72	-0.79	-0.60	-0.46	-0.37	-0.75	-0.82	-1.34	-1.40	-1.18	-1.16	-0.90	-0.77	-0.52	-0.52	-0.21	-0.05	-0.16	0.64
Kurtosis	3.73	4.18	3.83	4.45	3.57	3.85	3.56	3.23	3.51	3.68	4.12	3.88	6.24	6.06	4.75	4.55	4.13	4.03	2.97	3.09	3.34	4.17	5.47	8.78
Hit ratio	0.6140	0.5789	0.6316	0.6667	0.6140	0.6140	0.5263	0.5263	0.4912	0.5439	0.5614	0.5789	0.6140	0.6316	0.6140	0.5614	0.5614	0.5439	0.5789	0.5614	0.5789	0.5439	0.5088	0.5614
Maturity 2M																								
Avg. return	0.0026	0.0028	0.0033	0.0034	0.0028	0.0013	-0.0038	-0.0048	-0.0048	-0.0047	-0.0037	-0.0021	0.0032	0.0039	0.0049	0.0055	0.0050	0.0041	-0.0034	-0.0036	-0.0038	-0.0038	-0.0029	-0.0013
Avg. pos. return	0.0055	0.0104	0.0194	0.0231	0.0261	0.0295	0.0522	0.0483	0.0419	0.0380	0.0349	0.0317	0.0351	0.0387	0.0476	0.0512	0.0580	0.0580	0.0259	0.0206	0.0151	0.0113	0.0049	0.0025
Avg. neg. return	-0.0180	-0.0208	-0.0323	-0.0397	-0.0452	-0.0491	-0.0795	-0.0767	-0.0682	-0.0634	-0.0566	-0.0513	-0.0589	-0.0693	-0.0776	-0.0826	-0.0770	-0.0801	-0.0430	-0.0365	-0.0209	-0.0152	-0.0131	-0.0054
Max. loss	-0.0620	-0.0863	-0.1115	-0.1334	-0.1334	-0.1602	-0.2477	-0.2329	-0.2153	-0.1987	-0.1987	-0.1772	-0.2157	-0.2306	-0.2442	-0.2540	-0.2540	-0.2584	-0.1051	-0.0807	-0.0623	-0.0473	-0.0463	-0.0297
Volatility	0.0114	0.0195	0.0308	0.0359	0.0412	0.0486	0.0852	0.0805	0.0719	0.0675	0.0623	0.0552	0.0599	0.0670	0.0767	0.0808	0.0853	0.0886	0.0431	0.0352	0.0240	0.0193	0.0138	0.0065
Skewness	-3.24	-2.16	-1.56	-1.49	-1.02	-0.83	-0.55	-0.47	-0.41	-0.38	-0.59	-0.73	-0.97	-0.95	-0.84	-0.80	-0.63	-0.48	-0.44	-0.22	-0.04	0.09	-0.71	-2.16
Kurtosis	19.78	10.02	5.80	5.56	3.87	3.90	3.11	3.05	3.23	3.35	3.86	3.86	4.96	4.59	3.94	3.69	3.33	3.28	2.58	2.42	2.95	3.63	5.21	9.56
Hit ratio	0.8596	0.7368	0.6667	0.6667	0.6491	0.6140	0.5439	0.5439	0.5439	0.5439	0.5439	0.5614	0.6316	0.6491	0.6316	0.6316	0.5789	0.5789	0.5439	0.5439	0.4386	0.3860	0.5263	0.4912
Maturity 3M																								
Avg. return	0.0023	0.0025	0.0028	0.0029	0.0029	0.0016	-0.0035	-0.0040	-0.0044	-0.0044	-0.0040	-0.0025	0.0033	0.0040	0.0045	0.0048	0.0047	0.0039	-0.0033	-0.0034	-0.0034	-0.0034	-0.0030	-0.0015
Avg. pos. return	0.0079	0.0122	0.0179	0.0207	0.0235	0.0275	0.0499	0.0473	0.0425	0.0398	0.0368	0.0329	0.0371	0.0412	0.0461	0.0485	0.0520	0.0547	0.0234	0.0188	0.0140	0.0113	0.0075	0.0037
Avg. neg. return	-0.0112	-0.0189	-0.0307	-0.0363	-0.0431	-0.0483	-0.0756	-0.0733	-0.0679	-0.0646	-0.0597	-0.0543	-0.0626	-0.0683	-0.0764	-0.0799	-0.0805	-0.0813	-0.0393	-0.0335	-0.0226	-0.0178	-0.0133	-0.0073
Max. loss	-0.0695	-0.0880	-0.1077	-0.1271	-0.1271	-0.1549	-0.2388	-0.2292	-0.2167	-0.2032	-0.2032	-0.1815	-0.2211	-0.2313	-0.2412	-0.2492	-0.2492	-0.2549	-0.0953	-0.0769	-0.0574	-0.0495	-0.0470	-0.0324
Volatility	0.0139	0.0205	0.0290	0.0331	0.0376	0.0455	0.0813	0.0780	0.0719	0.0688	0.0649	0.0581	0.0630	0.0685	0.0752	0.0780	0.0815	0.0853	0.0390	0.0323	0.0238	0.0202	0.0159	0.0089
Skewness	-2.56	-1.89	-1.52	-1.52	-1.12	-0.98	-0.57	-0.52	-0.49	-0.46	-0.57	-0.62	-0.90	-0.87	-0.80	-0.79	-0.68	-0.57	-0.45	-0.29	-0.19	-0.09	-0.47	-1.12
Kurtosis	14.24	8.70	5.91	5.98	4.26	4.14	3.16	3.14	3.26	3.30	3.69	3.74	4.64	4.33	3.91	3.78	3.46	3.33	2.58	2.49	2.76	3.14	4.27	6.32
Hit ratio	0.6842	0.6667	0.6667	0.6667	0.6667	0.6316	0.5439	0.5439	0.5439	0.5439	0.5439	0.5614	0.6316	0.6316	0.6316	0.6316	0.6140	0.5965	0.5439	0.5439	0.4912	0.4561	0.4561	0.4912

Table 4 (continued)

	short straddle						long straddle						short strangle		long strangle	
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%
							Panel A: S&P 500									
Maturity 1M																
Avg. return	-0.0020	-0.0029	-0.0016	0.0023	0.0037	0.0019	-0.0016	-0.0002	-0.0004	-0.0032	-0.0040	-0.0013	0.0006	0.0002	-0.0011	-0.0006
Avg. pos. return	0.0150	0.0209	0.0352	0.0459	0.0554	0.0568	0.0498	0.0459	0.0355	0.0239	0.0160	0.0133	0.0330	0.0322	0.0269	0.0301
Avg. neg. return	-0.0289	-0.0408	-0.0703	-0.0673	-0.0698	-0.0724	-0.0664	-0.0586	-0.0308	-0.0324	-0.0275	-0.0212	-0.0660	-0.0573	-0.0425	-0.0420
Max. loss	-0.1408	-0.1957	-0.2375	-0.2644	-0.2644	-0.2758	-0.1725	-0.1577	-0.0987	-0.0987	-0.0987	-0.0734	-0.2396	-0.2346	-0.1311	-0.1263
Volatility	0.0301	0.0426	0.0649	0.0741	0.0826	0.0874	0.0770	0.0671	0.0444	0.0409	0.0309	0.0262	0.0621	0.0590	0.0454	0.0467
Skewness	-1.97	-1.92	-1.35	-1.39	-0.93	-0.73	-0.54	-0.33	0.19	0.14	-0.71	0.19	-1.40	-1.27	-0.44	-0.56
Kurtosis	9.45	8.99	5.11	5.09	3.98	3.98	2.89	2.82	3.04	3.73	4.24	7.29	5.90	6.17	3.44	3.02
Hit ratio	0.5965	0.5965	0.6316	0.5965	0.5614	0.5439	0.5263	0.5263	0.4211	0.4737	0.5088	0.5614	0.6491	0.6140	0.5614	0.5439
Maturity 2M																
Avg. return	0.0051	0.0057	0.0072	0.0080	0.0072	0.0053	-0.0067	-0.0078	-0.0080	-0.0080	-0.0062	-0.0030	0.0065	0.0047	-0.0070	-0.0052
Avg. pos. return	0.0104	0.0204	0.0372	0.0445	0.0511	0.0580	0.0458	0.0367	0.0307	0.0233	0.0103	0.0032	0.0365	0.0353	0.0269	0.0260
Avg. neg. return	-0.0337	-0.0362	-0.0593	-0.0721	-0.0769	-0.0767	-0.0776	-0.0684	-0.0383	-0.0284	-0.0207	-0.0094	-0.0604	-0.0546	-0.0422	-0.0475
Max. loss	-0.1160	-0.1560	-0.1942	-0.2240	-0.2240	-0.2512	-0.1887	-0.1494	-0.1138	-0.0894	-0.0865	-0.0561	-0.1983	-0.2071	-0.1144	-0.1133
Volatility	0.0220	0.0368	0.0571	0.0659	0.0755	0.0856	0.0772	0.0649	0.0457	0.0369	0.0265	0.0120	0.0572	0.0570	0.0465	0.0466
Skewness	-2.92	-1.88	-1.33	-1.22	-0.79	-0.53	-0.40	-0.17	0.06	0.23	-0.50	-2.20	-1.18	-1.05	-0.17	-0.46
Kurtosis	18.05	8.89	5.10	4.57	3.34	3.27	2.55	2.43	2.93	3.70	5.19	10.43	4.83	5.08	3.02	2.80
Hit ratio	0.8596	0.7193	0.6667	0.6667	0.6316	0.5789	0.5439	0.5439	0.4035	0.3509	0.4211	0.4737	0.6667	0.6316	0.4737	0.5439
Maturity 3M																
Avg. return	0.0046	0.0054	0.0061	0.0066	0.0067	0.0051	-0.0062	-0.0068	-0.0072	-0.0072	-0.0066	-0.0036	0.0065	0.0049	-0.0071	-0.0055
Avg. pos. return	0.0153	0.0237	0.0341	0.0393	0.0451	0.0518	0.0412	0.0340	0.0265	0.0227	0.0175	0.0058	0.0356	0.0343	0.0260	0.0256
Avg. neg. return	-0.0212	-0.0354	-0.0563	-0.0657	-0.0729	-0.0787	-0.0703	-0.0621	-0.0421	-0.0326	-0.0219	-0.0136	-0.0588	-0.0616	-0.0436	-0.0448
Max. loss	-0.1287	-0.1583	-0.1877	-0.2138	-0.2138	-0.2436	-0.1713	-0.1425	-0.1092	-0.0928	-0.0866	-0.0610	-0.1936	-0.2079	-0.1134	-0.1093
Volatility	0.0266	0.0386	0.0535	0.0603	0.0683	0.0794	0.0695	0.0595	0.0450	0.0384	0.0303	0.0170	0.0552	0.0570	0.0462	0.0456
Skewness	-2.28	-1.64	-1.29	-1.25	-0.90	-0.70	-0.41	-0.25	-0.10	0.02	-0.30	-0.90	-1.18	-1.10	-0.21	-0.37
Kurtosis	12.88	7.66	5.17	4.94	3.68	3.42	2.56	2.47	2.73	3.12	4.20	6.40	4.88	5.06	2.92	2.84
Hit ratio	0.6842	0.6667	0.6667	0.6667	0.6491	0.6140	0.5439	0.5439	0.4737	0.4211	0.3509	0.4737	0.6667	0.6667	0.4912	0.5263

Table 4 (continued)

	short butterfly		long butterfly		short put spread		long put spread		short put call spread		long put call spread	
	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM
						Panel A: S&P 500						
Maturity 1M												
Avg. return	-0.0025	-0.0032	-0.0057	-0.0054	-0.0005	0.0006	-0.0008	-0.0010	-0.0003	-0.0008	-0.0009	-0.0008
Avg. pos. return	0.0337	0.0386	0.0267	0.0273	0.0102	0.0416	0.0316	0.0220	0.0188	0.0204	0.0479	0.0495
Avg. neg. return	-0.0322	-0.0313	-0.0583	-0.0618	-0.0222	-0.0727	-0.0133	-0.0346	-0.0356	-0.0436	-0.0547	-0.0603
Max. loss	-0.1505	-0.1618	-0.1692	-0.1742	-0.0489	-0.2014	-0.0402	-0.1258	-0.0902	-0.0989	-0.2653	-0.2849
Volatility	0.0446	0.0472	0.0524	0.0544	0.0182	0.0713	0.0249	0.0381	0.0339	0.0360	0.0737	0.0803
Skewness	-0.47	-0.39	-1.14	-1.26	-1.11	-0.85	1.49	-0.57	-0.41	-0.79	-0.93	-1.03
Kurtosis	3.80	4.20	4.02	4.04	3.24	3.37	4.67	3.84	4.25	3.04	5.10	5.12
Hit ratio	0.4211	0.3684	0.5965	0.6140	0.6491	0.6140	0.2807	0.5614	0.6316	0.6491	0.4912	0.5088
Maturity 2M												
Avg. return	-0.0040	-0.0068	-0.0024	0.0002	-0.0003	0.0015	-0.0012	-0.0004	0.0002	0.0002	-0.0013	-0.0005
Avg. pos. return	0.0269	0.0340	0.0252	0.0261	0.0078	0.0412	0.0243	0.0222	0.0084	0.0124	0.0477	0.0511
Avg. neg. return	-0.0402	-0.0406	-0.0516	-0.0572	-0.0133	-0.0699	-0.0127	-0.0312	-0.0152	-0.0266	-0.0680	-0.0758
Max. loss	-0.1495	-0.1912	-0.1655	-0.1513	-0.0320	-0.1873	-0.0333	-0.1260	-0.0334	-0.0547	-0.2557	-0.2687
Volatility	0.0448	0.0523	0.0487	0.0476	0.0121	0.0673	0.0204	0.0370	0.0130	0.0214	0.0784	0.0846
Skewness	-0.63	-0.59	-1.23	-1.37	-0.69	-0.68	1.03	-0.65	-0.89	-1.23	-0.55	-0.58
Kurtosis	3.56	4.48	4.68	4.49	2.52	3.14	3.37	4.20	2.74	3.64	3.83	3.69
Hit ratio	0.5088	0.4211	0.6140	0.6667	0.5965	0.6140	0.3158	0.5439	0.6316	0.6667	0.5439	0.5614
Maturity 3M												
Avg. return	-0.0034	-0.0062	-0.0028	-0.0007	-0.0004	0.0011	-0.0009	0.0001	0.0000	0.0000	-0.0008	0.0000
Avg. pos. return	0.0248	0.0303	0.0231	0.0229	0.0053	0.0375	0.0155	0.0231	0.0062	0.0096	0.0489	0.0529
Avg. neg. return	-0.0439	-0.0488	-0.0527	-0.0495	-0.0098	-0.0646	-0.0103	-0.0361	-0.0100	-0.0181	-0.0733	-0.0770
Max. loss	-0.1485	-0.2027	-0.1618	-0.1401	-0.0232	-0.1757	-0.0255	-0.1288	-0.0250	-0.0417	-0.2613	-0.2700
Volatility	0.0441	0.0543	0.0469	0.0430	0.0088	0.0619	0.0152	0.0392	0.0094	0.0160	0.0812	0.0861
Skewness	-0.79	-0.86	-1.17	-1.24	-0.69	-0.66	0.94	-0.67	-0.94	-1.21	-0.59	-0.59
Kurtosis	3.67	4.60	4.64	4.41	2.60	3.15	3.25	3.89	3.06	3.65	3.72	3.59
Hit ratio	0.5614	0.5088	0.6316	0.6491	0.5965	0.6140	0.3684	0.5789	0.5965	0.6316	0.5614	0.5614

Table 4 (continued)

	short call						long call						short put						long put					
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%
Panel B: DAX																								
Maturity 1M																								
Avg. return	0.0000	0.0045	0.0049	0.0049	0.0063	0.0047	0.0005	-0.0029	0.0009	0.0011	0.0014	0.0029	0.0032	0.0068	0.0054	0.0093	0.0144	0.0027	0.0022	0.0018	-0.0031	-0.0028	-0.0119	-0.0031
Avg. pos. return	0.0245	0.0302	0.0326	0.0336	0.0394	0.0411	0.0600	0.0554	0.0509	0.0477	0.0425	0.0428	0.0410	0.0428	0.0533	0.0584	0.0613	0.0566	0.0402	0.0367	0.0287	0.0273	0.0254	0.0299
Avg. neg. return	-0.0361	-0.0351	-0.0415	-0.0474	-0.0502	-0.0495	-0.0793	-0.0790	-0.0647	-0.0558	-0.0521	-0.0484	-0.0532	-0.0607	-0.0777	-0.0760	-0.0677	-0.0634	-0.0434	-0.0431	-0.0410	-0.0382	-0.0400	-0.0468
Max. loss	-0.1252	-0.1021	-0.1348	-0.1460	-0.1499	-0.1507	-0.2181	-0.1980	-0.1722	-0.1654	-0.1572	-0.1508	-0.2193	-0.2469	-0.2224	-0.2646	-0.2623	-0.2609	-0.1508	-0.1373	-0.1263	-0.1227	-0.1680	-0.1568
Volatility	0.0406	0.0401	0.0458	0.0492	0.0552	0.0578	0.0898	0.0878	0.0782	0.0727	0.0659	0.0617	0.0638	0.0678	0.0804	0.0829	0.0839	0.0837	0.0560	0.0525	0.0466	0.0423	0.0445	0.0479
Skewness	-0.33	-0.59	-0.80	-0.90	-0.71	-0.64	0.00	0.01	0.27	0.36	0.22	-0.13	-0.75	-1.00	-0.66	-0.76	-0.52	-0.20	-0.27	-0.24	-0.23	-0.12	-0.62	-0.91
Kurtosis	4.02	3.22	3.91	3.98	3.45	3.44	4.04	3.89	4.41	5.01	5.37	4.48	5.15	5.91	3.51	4.19	4.33	4.47	3.89	3.91	3.84	3.88	4.62	4.10
Hit ratio	0.5614	0.5965	0.6140	0.6316	0.6140	0.5789	0.5614	0.5439	0.5439	0.5263	0.5439	0.5439	0.5789	0.6316	0.6140	0.6140	0.6140	0.5263	0.5263	0.5439	0.5263	0.5263	0.4211	0.5614
Maturity 2M																								
Avg. return	0.0064	0.0061	0.0049	0.0054	0.0061	0.0050	-0.0094	-0.0047	0.0006	0.0007	0.0013	0.0019	0.0065	0.0085	0.0110	0.0106	0.0171	0.0066	0.0013	0.0002	-0.0024	-0.0031	-0.0100	-0.0056
Avg. pos. return	0.0264	0.0197	0.0207	0.0262	0.0315	0.0381	0.0506	0.0611	0.0599	0.0559	0.0497	0.0433	0.0449	0.0484	0.0566	0.0601	0.0694	0.0658	0.0367	0.0314	0.0235	0.0191	0.0150	0.0268
Avg. neg. return	-0.0195	-0.0308	-0.0439	-0.0438	-0.0495	-0.0481	-0.0779	-0.0740	-0.0656	-0.0610	-0.0567	-0.0514	-0.0598	-0.0724	-0.0816	-0.0897	-0.0736	-0.0762	-0.0411	-0.0346	-0.0273	-0.0242	-0.0233	-0.0359
Max. loss	-0.0812	-0.0910	-0.1228	-0.1377	-0.1448	-0.1503	-0.2299	-0.2000	-0.1836	-0.1754	-0.1683	-0.1560	-0.1876	-0.2227	-0.2574	-0.2591	-0.2270	-0.4767	-0.1058	-0.1094	-0.1122	-0.1197	-0.1286	-0.1436
Volatility	0.0315	0.0317	0.0352	0.0409	0.0473	0.0536	0.0882	0.0902	0.0833	0.0787	0.0736	0.0648	0.0677	0.0751	0.0839	0.0894	0.0891	0.1065	0.0500	0.0428	0.0356	0.0325	0.0316	0.0435
Skewness	0.36	-0.28	-1.45	-1.35	-1.09	-0.86	-0.23	0.11	0.23	0.32	0.34	-0.01	-0.66	-0.79	-0.77	-0.72	-0.39	-1.50	-0.02	0.22	0.00	-0.25	-1.07	-0.73
Kurtosis	4.08	5.50	6.21	5.34	4.18	3.50	3.92	4.01	4.18	4.55	4.87	4.53	4.37	4.34	4.20	3.72	3.41	9.34	3.33	3.80	5.06	6.59	7.39	4.07
Hit ratio	0.5614	0.7193	0.7368	0.6842	0.6667	0.5965	0.5088	0.4912	0.5088	0.5088	0.5263	0.5439	0.6140	0.6491	0.6491	0.6491	0.6140	0.5614	0.5263	0.5088	0.4737	0.4737	0.3333	0.4737
Maturity 3M																								
Avg. return	0.0092	0.0046	0.0033	0.0042	0.0041	0.0048	-0.0100	-0.0017	0.0025	0.0027	0.0003	0.0024	0.0067	0.0082	0.0103	0.0108	0.0137	0.0104	0.0008	-0.0002	0.0002	-0.0023	-0.0066	-0.0107
Avg. pos. return	0.0293	0.0166	0.0190	0.0227	0.0265	0.0334	0.0508	0.0537	0.0577	0.0556	0.0488	0.0455	0.0454	0.0503	0.0560	0.0584	0.0628	0.0648	0.0320	0.0293	0.0230	0.0196	0.0154	0.0208
Avg. neg. return	-0.0234	-0.0233	-0.0342	-0.0396	-0.0450	-0.0488	-0.0728	-0.0789	-0.0687	-0.0655	-0.0582	-0.0533	-0.0657	-0.0709	-0.0755	-0.0787	-0.0782		-0.0394	-0.0331	-0.0287	-0.0249	-0.0224	-0.0285
Max. loss	-0.0722	-0.0824	-0.1114	-0.1257	-0.1367	-0.1465	-0.2162	-0.2058	-0.1834	-0.1822	-0.1675	-0.1570	-0.1970	-0.2361	-0.2365	-0.2376	-0.2244	-0.4767	-0.1042	-0.1262	-0.1182	-0.1228	-0.1349	-0.1459
Volatility	0.0343	0.0255	0.0316	0.0367	0.0421	0.0497	0.0833	0.0867	0.0838	0.0812	0.0702	0.0684	0.0708	0.0765	0.0817	0.0843	0.0863	0.1065	0.0460	0.0412	0.0371	0.0329	0.0307	0.0357
Skewness	-0.14	-1.32	-1.76	-1.33	-1.36	-1.07	-0.29	-0.16	0.06	0.13	-0.38	0.12	-0.64	-0.70	-0.60	-0.56	-0.44	-1.79	0.01	-0.12	-0.62	-0.59	-1.25	-0.80
Kurtosis	2.92	6.04	6.32	5.46	4.83	3.95	3.85	3.57	3.84	4.05	3.19	4.65	4.34	4.39	4.02	3.78	3.59	9.79	3.36	4.19	5.64	6.28	8.42	5.78
Hit ratio	0.5965	0.6842	0.6842	0.6842	0.6667	0.6316	0.4912	0.5614	0.5439	0.5439	0.5263	0.5439	0.6316	0.6316	0.6316	0.6316	0.6316	0.5965	0.5439	0.5088	0.5439	0.4912	0.4035	0.3509

Table 4 (continued)

	short straddle						long straddle						short strangle		long strangle	
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%
									Panel B: DAX							
Maturity 1M																
Avg. return	-0.0013	0.0064	0.0054	0.0093	0.0161	0.0030	-0.0011	-0.0050	-0.0061	-0.0057	-0.0143	-0.0042	0.0088	0.0037	-0.0009	0.0010
Avg. pos. return	0.0263	0.0344	0.0432	0.0504	0.0605	0.0543	0.0586	0.0501	0.0440	0.0323	0.0311	0.0303	0.0439	0.0428	0.0370	0.0407
Avg. neg. return	-0.0387	-0.0402	-0.0694	-0.0728	-0.0671	-0.0646	-0.0756	-0.0770	-0.0489	-0.0455	-0.0421	-0.0499	-0.0562	-0.0505	-0.0502	-0.0467
Max. loss	-0.1359	-0.1904	-0.1946	-0.2452	-0.2508	-0.2579	-0.1739	-0.2034	-0.1537	-0.1269	-0.1687	-0.1569	-0.2346	-0.2159	-0.1419	-0.1510
Volatility	0.0445	0.0493	0.0669	0.0722	0.0796	0.0813	0.0869	0.0815	0.0656	0.0552	0.0515	0.0506	0.0646	0.0628	0.0600	0.0589
Skewness	-0.61	-1.30	-1.00	-1.16	-0.73	-0.40	0.13	0.16	0.48	0.85	0.02	-0.74	-1.19	-0.90	0.43	0.03
Kurtosis	4.28	6.54	3.75	4.67	3.99	4.15	3.88	3.90	4.78	6.24	5.57	4.11	5.78	4.78	5.51	4.47
Hit ratio	0.5439	0.6140	0.6491	0.6491	0.6316	0.5439	0.5439	0.5439	0.4386	0.4912	0.3684	0.5614	0.6316	0.5614	0.5439	0.5263
Maturity 2M																
Avg. return	0.0078	0.0091	0.0103	0.0106	0.0180	0.0068	-0.0118	-0.0082	-0.0056	-0.0062	-0.0125	-0.0077	0.0100	0.0072	-0.0025	-0.0009
Avg. pos. return	0.0283	0.0297	0.0380	0.0480	0.0609	0.0619	0.0544	0.0504	0.0400	0.0379	0.0393	0.0273	0.0425	0.0434	0.0397	0.0379
Avg. neg. return	-0.0312	-0.0531	-0.0762	-0.0786	-0.0689	-0.0761	-0.0647	-0.0657	-0.0495	-0.0357	-0.0288	-0.0405	-0.0674	-0.0556	-0.0463	-0.0474
Max. loss	-0.0900	-0.1599	-0.2186	-0.2284	-0.2033	-0.4758	-0.1890	-0.1607	-0.1362	-0.1323	-0.1337	-0.1441	-0.1978	-0.1872	-0.1149	-0.1141
Volatility	0.0395	0.0485	0.0614	0.0719	0.0777	0.1014	0.0804	0.0755	0.0605	0.0528	0.0453	0.0464	0.0646	0.0628	0.0588	0.0564
Skewness	0.24	-0.83	-1.44	-1.21	-0.61	-1.92	0.02	0.50	0.78	0.95	0.72	-0.44	-1.21	-0.99	0.95	0.37
Kurtosis	4.39	6.14	5.93	4.42	3.50	10.48	3.56	4.10	5.14	6.72	7.21	3.84	4.79	4.25	5.42	4.24
Hit ratio	0.6491	0.7368	0.7368	0.6842	0.6491	0.5789	0.4211	0.4737	0.4737	0.3860	0.2281	0.4737	0.6842	0.6140	0.4912	0.5263
Maturity 3M																
Avg. return	0.0106	0.0072	0.0079	0.0094	0.0125	0.0102	-0.0129	-0.0057	-0.0013	-0.0035	-0.0100	-0.0123	0.0074	0.0070	-0.0039	-0.0010
Avg. pos. return	0.0356	0.0279	0.0345	0.0424	0.0527	0.0569	0.0446	0.0442	0.0412	0.0358	0.0244	0.0273	0.0386	0.0414	0.0367	0.0380
Avg. neg. return	-0.0331	-0.0418	-0.0614	-0.0632	-0.0629		-0.0643	-0.0615	-0.0452	-0.0413	-0.0332	-0.0331	-0.0613	-0.0575	-0.0461	-0.0445
Max. loss	-0.1244	-0.1799	-0.1977	-0.1974	-0.2003	-0.4737	-0.1775	-0.1822	-0.1620	-0.1439	-0.1469	-0.1486	-0.2113	-0.1841	-0.1388	-0.1173
Volatility	0.0440	0.0440	0.0550	0.0623	0.0692	0.0986	0.0712	0.0698	0.0600	0.0540	0.0411	0.0423	0.0604	0.0617	0.0533	0.0558
Skewness	-0.60	-1.68	-1.52	-1.12	-0.98	-2.39	-0.07	0.06	0.14	0.54	-0.55	-0.05	-1.41	-1.20	-0.03	0.53
Kurtosis	3.78	7.85	5.76	4.49	3.78	12.03	3.58	3.60	4.74	5.09	4.81	5.07	5.41	4.62	3.22	4.62
Hit ratio	0.6140	0.6842	0.7018	0.6667	0.6316	0.6316	0.4561	0.5088	0.4912	0.4737	0.3860	0.3333	0.6667	0.6316	0.4912	0.5088

Table 4 (continued)

	short butterfly		long butterfly		short put spread		long put spread		short put call spread		long put call spread	
	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM
						Panel B: DAX						
Maturity 1M												
Avg. return	-0.0011	-0.0081	-0.0048	0.0005	-0.0025	0.0033	-0.0086	-0.0008	0.0025	0.0029	-0.0001	0.0034
Avg. pos. return	0.0371	0.0482	0.0360	0.0442	0.0113	0.0488	0.0213	0.0319	0.0264	0.0294	0.0540	0.0538
Avg. neg. return	-0.0509	-0.0588	-0.0529	-0.0477	-0.0305	-0.0759	-0.0183	-0.0457	-0.0371	-0.0381	-0.0616	-0.0676
Max. loss	-0.1296	-0.1599	-0.1629	-0.1632	-0.1306	-0.1700	-0.0733	-0.2281	-0.1215	-0.1349	-0.2423	-0.2681
Volatility	0.0589	0.0710	0.0577	0.0605	0.0273	0.0761	0.0207	0.0548	0.0392	0.0421	0.0815	0.0848
Skewness	-0.27	0.02	-0.90	-0.69	-2.81	-0.48	0.40	-1.17	-0.86	-0.83	0.05	-0.15
Kurtosis	2.92	2.83	3.70	3.09	12.21	3.09	4.31	7.42	3.97	4.02	4.95	5.25
Hit ratio	0.5439	0.4386	0.5263	0.5263	0.6491	0.6140	0.2456	0.5614	0.6140	0.5965	0.5088	0.5614
Maturity 2M												
Avg. return	-0.0004	-0.0018	-0.0068	-0.0097	0.0007	0.0077	-0.0052	0.0011	0.0012	0.0021	0.0030	0.0050
Avg. pos. return	0.0410	0.0683	0.0231	0.0204	0.0071	0.0501	0.0203	0.0310	0.0098	0.0150	0.0611	0.0652
Avg. neg. return	-0.0459	-0.0479	-0.0556	-0.0495	-0.0161	-0.0718	-0.0150	-0.0372	-0.0189	-0.0283	-0.0721	-0.0786
Max. loss	-0.1342	-0.1411	-0.1544	-0.1800	-0.0510	-0.2166	-0.0308	-0.1420	-0.0818	-0.0781	-0.2175	-0.2537
Volatility	0.0569	0.0704	0.0507	0.0478	0.0131	0.0741	0.0216	0.0473	0.0174	0.0240	0.0898	0.0962
Skewness	-0.02	0.36	-0.96	-1.51	-1.71	-0.59	2.56	-0.38	-2.19	-1.37	0.03	-0.14
Kurtosis	3.67	2.83	4.19	5.44	6.30	3.76	11.79	4.56	10.69	4.58	4.37	4.26
Hit ratio	0.5088	0.3860	0.5965	0.5439	0.7018	0.6316	0.2807	0.5439	0.6842	0.6842	0.5439	0.5614
Maturity 3M												
Avg. return	0.0002	0.0052	-0.0072	-0.0123	-0.0001	0.0064	-0.0027	0.0032	-0.0006	0.0002	0.0051	0.0066
Avg. pos. return	0.0365	0.0670	0.0239	0.0197	0.0053	0.0476	0.0202	0.0319	0.0063	0.0107	0.0638	0.0689
Avg. neg. return	-0.0431	-0.0549	-0.0425	-0.0428	-0.0096	-0.0599	-0.0131	-0.0364	-0.0144	-0.0179	-0.0765	-0.0799
Max. loss	-0.1373	-0.1628	-0.1485	-0.1474	-0.0376	-0.1785	-0.0383	-0.1337	-0.0876	-0.0653	-0.2275	-0.2627
Volatility	0.0522	0.0768	0.0469	0.0434	0.0097	0.0678	0.0242	0.0473	0.0149	0.0178	0.0933	0.0984
Skewness	-0.43	0.16	-1.19	-1.12	-1.63	-0.37	3.38	-0.53	-3.67	-1.50	-0.13	-0.20
Kurtosis	3.58	2.79	4.17	4.24	6.47	3.50	18.28	4.91	21.22	5.20	4.03	3.99
Hit ratio	0.5263	0.4737	0.5088	0.4737	0.6140	0.5965	0.3158	0.5614	0.6491	0.6140	0.5614	0.5614

Table 4 (continued)

	short call						long call						short put						long put					
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%
	Panel C: EURO STOXX 50																							
Maturity 1M																								
Avg. return	-0.0039	-0.0030	-0.0019	-0.0014	-0.0095	-0.0026	-0.0081	-0.0063	-0.0062	-0.0067	-0.0053	-0.0041	-0.0026	-0.0023	0.0024	0.0024	0.0017	0.0035	-0.0041	-0.0052	-0.0074	-0.0068	-0.0090	-0.0088
Avg. pos. return	0.0213	0.0232	0.0264	0.0318	0.0359	0.0375	0.0596	0.0599	0.0505	0.0447	0.0396	0.0374	0.0379	0.0427	0.0479	0.0574	0.0648	0.0653	0.0354	0.0344	0.0225	0.0215	0.0216	0.0182
Avg. neg. return	-0.0323	-0.0373	-0.0488	-0.0431	-0.0596	-0.0476	-0.0706	-0.0633	-0.0554	-0.0509	-0.0495	-0.0475	-0.0514	-0.0564	-0.0708	-0.0645	-0.0649	-0.0579	-0.0454	-0.0386	-0.0408	-0.0376	-0.0320	-0.0332
Max. loss	-0.0672	-0.0875	-0.1249	-0.1349	-0.4008	-0.1420	-0.2308	-0.2020	-0.1771	-0.1702	-0.1595	-0.1508	-0.2220	-0.2433	-0.2488	-0.2567	-0.2655	-0.2425	-0.1392	-0.1131	-0.0948	-0.1070	-0.1007	-0.0949
Volatility	0.0334	0.0376	0.0449	0.0477	0.0747	0.0558	0.0893	0.0825	0.0730	0.0664	0.0623	0.0574	0.0614	0.0690	0.0771	0.0817	0.0862	0.0853	0.0533	0.0470	0.0395	0.0380	0.0350	0.0362
Skewness	-0.07	-0.38	-0.79	-0.82	-2.73	-0.47	-0.32	-0.10	0.22	0.04	0.04	-0.37	-0.85	-0.98	-0.88	-0.70	-0.51	-0.18	-0.31	0.02	0.12	-0.23	-0.24	-0.19
Kurtosis	2.42	2.79	3.26	3.52	14.51	3.37	3.42	3.60	4.28	4.09	4.63	3.76	5.09	4.89	4.21	3.86	3.66	4.20	3.53	3.34	3.40	3.47	3.30	3.40
Hit ratio	0.5263	0.5614	0.6140	0.5439	0.5088	0.5088	0.4561	0.4386	0.4386	0.4386	0.4737	0.4912	0.5263	0.5263	0.5965	0.5263	0.4912	0.4737	0.4912	0.4386	0.5088	0.5088	0.4211	0.4737
Maturity 2M																								
Avg. return	-0.0003	0.0001	0.0018	0.0014	0.0010	-0.0009	-0.0097	-0.0109	-0.0103	-0.0093	-0.0080	-0.0062	-0.0003	-0.0008	0.0005	-0.0001	-0.0021	-0.0022	-0.0059	-0.0059	-0.0066	-0.0058	-0.0054	-0.0059
Avg. pos. return	0.0088	0.0123	0.0193	0.0232	0.0322	0.0362	0.0671	0.0633	0.0555	0.0520	0.0469	0.0382	0.0430	0.0451	0.0548	0.0599	0.0648	0.0740	0.0336	0.0269	0.0177	0.0136	0.0137	0.0156
Avg. neg. return	-0.0134	-0.0340	-0.0433	-0.0465	-0.0394	-0.0456	-0.0745	-0.0734	-0.0657	-0.0608	-0.0542	-0.0524	-0.0525	-0.0696	-0.0751	-0.0782	-0.0830	-0.0715	-0.0392	-0.0333	-0.0230	-0.0186	-0.0146	-0.0131
Max. loss	-0.0437	-0.0782	-0.1119	-0.1238	-0.1310	-0.1385	-0.2240	-0.2091	-0.1915	-0.1852	-0.1734	-0.1607	-0.1865	-0.2761	-0.2259	-0.2481	-0.2973	-0.2670	-0.1037	-0.0735	-0.0727	-0.0612	-0.0774	-0.1537
Volatility	0.0169	0.0268	0.0357	0.0408	0.0461	0.0528	0.0938	0.0882	0.0788	0.0744	0.0686	0.0611	0.0654	0.0785	0.0845	0.0911	0.0977	0.0987	0.0466	0.0367	0.0262	0.0216	0.0218	0.0266
Skewness	1.18	-0.80	-1.19	-1.16	-0.99	-0.67	-0.17	0.04	0.16	0.17	0.15	-0.16	-0.63	-1.05	-0.63	-0.67	-0.65	-0.34	-0.11	0.33	0.51	0.50	0.36	-2.64
Kurtosis	10.62	5.67	5.03	4.34	3.62	3.21	3.41	3.40	3.78	3.96	4.30	3.98	4.09	5.18	3.48	3.60	3.71	3.67	3.02	3.06	4.56	4.96	7.40	19.06
Hit ratio	0.5789	0.7193	0.7018	0.6667	0.5439	0.5263	0.4386	0.4386	0.4386	0.4386	0.4386	0.4912	0.5263	0.5789	0.5614	0.5439	0.5263	0.4561	0.4386	0.4386	0.3860	0.3860	0.3158	0.2456
Maturity 3M																								
Avg. return	-0.0012	-0.0014	-0.0008	-0.0010	-0.0010	-0.0018	-0.0090	-0.0081	-0.0087	-0.0072	-0.0068	-0.0057	0.0003	0.0004	0.0014	-0.0047	0.0009	0.0000	-0.0066	-0.0063	-0.0073	-0.0073	-0.0073	-0.0068
Avg. pos. return	0.0095	0.0117	0.0172	0.0198	0.0275	0.0329	0.0645	0.0605	0.0534	0.0534	0.0492	0.0427	0.0460	0.0511	0.0574	0.0595	0.0622	0.0705	0.0301	0.0239	0.0168	0.0151	0.0109	0.0102
Avg. neg. return	-0.0170	-0.0299	-0.0402	-0.0430	-0.0379	-0.0435	-0.0708	-0.0659	-0.0612	-0.0582	-0.0540	-0.0495	-0.0549	-0.0608	-0.0661	-0.0822	-0.0730	-0.0687	-0.0374	-0.0314	-0.0249	-0.0201	-0.0170	-0.0121
Max. loss	-0.0638	-0.0870	-0.1106	-0.1184	-0.1301	-0.1410	-0.2151	-0.1950	-0.1770	-0.1706	-0.1609	-0.1521	-0.1964	-0.2125	-0.2266	-0.5271	-0.2349	-0.2356	-0.0991	-0.0741	-0.0793	-0.0686	-0.0590	-0.0705
Volatility	0.0183	0.0251	0.0338	0.0378	0.0428	0.0498	0.0886	0.0836	0.0761	0.0738	0.0694	0.0628	0.0686	0.0765	0.0822	0.1075	0.0882	0.0915	0.0429	0.0342	0.0270	0.0231	0.0192	0.0167
Skewness	-1.18	-1.46	-1.47	-1.37	-1.21	-0.88	-0.20	-0.10	0.03	0.04	0.07	-0.06	-0.58	-0.68	-0.55	-2.13	-0.45	-0.23	-0.16	0.12	0.03	0.10	0.07	-0.22
Kurtosis	4.95	4.96	4.87	4.59	4.12	3.64	3.50	3.56	3.81	3.77	4.00	3.98	4.09	4.17	3.69	11.37	3.49	3.38	2.92	2.88	3.77	4.08	4.62	8.26
Hit ratio	0.5789	0.6667	0.6667	0.6491	0.5439	0.5263	0.4386	0.4386	0.4386	0.4386	0.4386	0.4561	0.5263	0.5263	0.5263	0.5263	0.5263	0.4737	0.4386	0.4386	0.4035	0.3509	0.3333	0.2281

Table 4 (continued)

	short straddle						long straddle						short strangle		long strangle	
	90%	95%	100%	102%	105%	110%	90%	95%	100%	102%	105%	110%	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%
							Panel C: EURO STOXX 50									
Maturity 1M																
Avg. return	-0.0039	-0.0029	0.0029	0.0033	-0.0048	0.0038	-0.0090	-0.0083	-0.0105	-0.0103	-0.0111	-0.0098	-0.0088	-0.0023	-0.0075	-0.0052
Avg. pos. return	0.0236	0.0261	0.0410	0.0457	0.0658	0.0658	0.0571	0.0525	0.0367	0.0272	0.0243	0.0181	0.0406	0.0385	0.0351	0.0350
Avg. neg. return	-0.0349	-0.0548	-0.0661	-0.0695	-0.0734	-0.0578	-0.0701	-0.0607	-0.0435	-0.0398	-0.0346	-0.0333	-0.0718	-0.0513	-0.0438	-0.0471
Max. loss	-0.1257	-0.1891	-0.2182	-0.2336	-0.3907	-0.2390	-0.1975	-0.1570	-0.1100	-0.1128	-0.1023	-0.0951	-0.4002	-0.2179	-0.1147	-0.1394
Volatility	0.0379	0.0495	0.0651	0.0725	0.0976	0.0846	0.0858	0.0733	0.0552	0.0460	0.0398	0.0364	0.0845	0.0608	0.0535	0.0544
Skewness	-0.58	-1.20	-1.14	-0.99	-1.41	-0.23	-0.20	0.26	0.91	0.46	0.55	-0.14	-2.25	-0.87	0.57	-0.24
Kurtosis	3.58	5.25	4.60	4.04	6.25	3.94	3.25	3.50	5.42	4.74	5.40	3.34	10.18	4.84	4.95	3.66
Hit ratio	0.5263	0.6316	0.6316	0.6140	0.4737	0.4737	0.4561	0.4386	0.3860	0.4211	0.3860	0.4561	0.5439	0.5263	0.4386	0.4912
Maturity 2M																
Avg. return	0.0014	0.0009	0.0039	0.0030	0.0007	-0.0007	-0.0123	-0.0134	-0.0135	-0.0117	-0.0101	-0.0088	0.0028	0.0017	-0.0107	-0.0090
Avg. pos. return	0.0149	0.0226	0.0368	0.0437	0.0595	0.0712	0.0593	0.0508	0.0352	0.0310	0.0278	0.0167	0.0372	0.0409	0.0346	0.0342
Avg. neg. return	-0.0199	-0.0665	-0.0813	-0.0870	-0.0755	-0.0708	-0.0725	-0.0635	-0.0440	-0.0325	-0.0219	-0.0165	-0.0797	-0.0529	-0.0435	-0.0453
Max. loss	-0.0900	-0.2256	-0.1800	-0.2353	-0.2734	-0.2552	-0.1877	-0.1366	-0.1012	-0.0961	-0.0898	-0.1668	-0.2696	-0.1721	-0.1017	-0.1167
Volatility	0.0260	0.0507	0.0641	0.0758	0.0871	0.0947	0.0848	0.0702	0.0503	0.0412	0.0333	0.0297	0.0694	0.0621	0.0506	0.0519
Skewness	-0.34	-2.05	-1.22	-1.23	-1.00	-0.52	-0.02	0.43	0.87	1.01	0.72	-2.71	-1.59	-0.83	0.75	0.12
Kurtosis	8.29	9.31	4.11	4.18	3.68	3.35	3.10	3.24	4.88	5.79	7.26	16.15	6.29	3.79	4.71	3.55
Hit ratio	0.5965	0.7368	0.7018	0.6667	0.5439	0.4737	0.4386	0.4211	0.3684	0.3158	0.2281	0.2281	0.6842	0.5614	0.4035	0.4386
Maturity 3M																
Avg. return	0.0009	0.0006	0.0023	-0.0041	0.0019	0.0007	-0.0121	-0.0110	-0.0126	-0.0111	-0.0108	-0.0092	0.0018	0.0013	-0.0098	-0.0092
Avg. pos. return	0.0163	0.0224	0.0331	0.0419	0.0525	0.0644	0.0532	0.0449	0.0312	0.0264	0.0247	0.0203	0.0357	0.0404	0.0311	0.0326
Avg. neg. return	-0.0303	-0.0563	-0.0711	-0.0783	-0.0635	-0.0660	-0.0670	-0.0545	-0.0423	-0.0364	-0.0256	-0.0158	-0.0672	-0.0531	-0.0441	-0.0442
Max. loss	-0.1181	-0.1575	-0.1949	-0.5136	-0.2210	-0.2311	-0.1790	-0.1343	-0.1147	-0.0933	-0.0779	-0.0735	-0.1975	-0.1912	-0.1091	-0.1187
Volatility	0.0302	0.0459	0.0601	0.0931	0.0747	0.0849	0.0758	0.0622	0.0477	0.0411	0.0329	0.0224	0.0635	0.0623	0.0482	0.0497
Skewness	-1.54	-1.62	-1.27	-3.18	-0.95	-0.51	-0.06	0.27	0.52	0.64	0.87	0.23	-1.34	-1.00	0.55	0.16
Kurtosis	6.51	5.98	4.53	17.15	3.70	3.17	3.15	3.23	4.24	4.57	6.02	5.72	4.89	4.23	4.07	3.58
Hit ratio	0.6491	0.7018	0.6842	0.5965	0.5439	0.4912	0.4386	0.4211	0.3860	0.3860	0.2807	0.1754	0.6491	0.5614	0.4386	0.4386

Table 4 (continued)

	short butterfly		long butterfly		short put spread		long put spread		short put call spread		long put call spread	
	ATM +- 5%	ATM +- 10%	ATM +- 5%	ATM +- 10%	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM	short put 5% OTM	short put 10% OTM	long put 5% OTM	long put 10% OTM
Panel C: EURO STOXX 50												
Maturity 1M												
Avg. return	-0.0161	-0.0118	-0.0069	-0.0071	0.0015	0.0011	-0.0047	-0.0072	-0.0040	-0.0029	-0.0058	-0.0053
Avg. pos. return	0.0334	0.0353	0.0300	0.0388	0.0115	0.0448	0.0257	0.0283	0.0224	0.0267	0.0522	0.0571
Avg. neg. return	-0.0583	-0.0498	-0.0608	-0.0606	-0.0220	-0.0693	-0.0176	-0.0443	-0.0363	-0.0395	-0.0560	-0.0593
Max. loss	-0.3948	-0.1485	-0.1572	-0.1709	-0.0421	-0.1727	-0.0332	-0.1194	-0.0992	-0.1252	-0.2472	-0.2669
Volatility	0.0740	0.0575	0.0566	0.0645	0.0169	0.0723	0.0229	0.0468	0.0361	0.0421	0.0770	0.0838
Skewness	-2.39	0.40	-0.94	-0.88	-1.00	-0.62	1.25	-0.17	-0.61	-0.83	-0.11	-0.32
Kurtosis	13.35	4.32	3.38	3.37	2.64	3.27	3.52	3.38	2.94	3.40	4.94	4.69
Hit ratio	0.4386	0.4211	0.5789	0.5263	0.6842	0.5965	0.2982	0.4912	0.5439	0.5439	0.4386	0.4386
Maturity 2M												
Avg. return	-0.0111	-0.0157	-0.0076	-0.0045	-0.0017	-0.0027	-0.0020	-0.0053	-0.0008	-0.0010	-0.0074	-0.0077
Avg. pos. return	0.0305	0.0352	0.0244	0.0251	0.0088	0.0495	0.0258	0.0264	0.0093	0.0144	0.0622	0.0637
Avg. neg. return	-0.0463	-0.0502	-0.0552	-0.0598	-0.0152	-0.0656	-0.0147	-0.0361	-0.0154	-0.0254	-0.0662	-0.0774
Max. loss	-0.1321	-0.1549	-0.1471	-0.1717	-0.0402	-0.1791	-0.0339	-0.2183	-0.0379	-0.0769	-0.2264	-0.2935
Volatility	0.0499	0.0537	0.0514	0.0530	0.0153	0.0743	0.0226	0.0476	0.0158	0.0253	0.0860	0.0972
Skewness	-0.49	0.12	-0.95	-1.43	-0.92	-0.48	1.15	-1.43	0.18	-0.98	0.00	-0.35
Kurtosis	3.08	3.65	3.80	4.56	3.09	3.07	3.60	9.07	5.14	4.31	4.03	4.30
Hit ratio	0.4386	0.3860	0.5789	0.6316	0.5439	0.5263	0.3158	0.4737	0.5789	0.5965	0.4386	0.4737
Maturity 3M												
Avg. return	-0.0108	-0.0139	-0.0083	-0.0076	-0.0010	-0.0025	-0.0023	-0.0047	-0.0035	-0.0040	-0.0053	-0.0050
Avg. pos. return	0.0300	0.0348	0.0273	0.0290	0.0072	0.0451	0.0153	0.0292	0.0064	0.0100	0.0610	0.0616
Avg. neg. return	-0.0429	-0.0496	-0.0454	-0.0457	-0.0088	-0.0599	-0.0117	-0.0356	-0.0123	-0.0220	-0.0656	-0.0749
Max. loss	-0.1343	-0.1437	-0.1462	-0.1501	-0.0302	-0.1699	-0.0294	-0.1569	-0.0542	-0.0614	-0.2229	-0.2405
Volatility	0.0479	0.0556	0.0505	0.0506	0.0105	0.0680	0.0162	0.0455	0.0130	0.0207	0.0866	0.0936
Skewness	-0.52	-0.17	-0.86	-1.02	-0.54	-0.43	1.03	-0.62	-1.42	-1.22	-0.12	-0.24
Kurtosis	3.19	3.15	3.81	3.92	3.40	3.22	4.03	4.75	5.82	3.83	4.05	4.03
Hit ratio	0.4211	0.4035	0.4912	0.4912	0.4737	0.5263	0.3509	0.4561	0.4561	0.5439	0.4561	0.4912

Table 5 Risk-Adjusted Performance using the Omega ratio

This table shows the performance of option strategies, based on their Omega ratio $\Omega_i = \left(\int_x^b [1 - F(r_i)]dr\right) / \left(\int_L^x F(r_i)dr\right)$, where the nominator is one minus the cumulative distribution function exceeding threshold *x*. The denominator is the cumulative distribution function for returns up to threshold *x*. Here, this threshold equals to 0. The period covered is from January 2006 to September 2010.

		S&P 500			DAX			EURO STOXX 50		
Strategy	Strike	1M	2M	3M	1M	2M	3M	1M	2M	3M
short call	90%	0.893	2.188	1.691	0.997	1.758	2.015	0.739	0.944	0.827
	95%	0.851	1.550	1.423	1.329	1.747	1.670	0.813	1.012	0.853
	100%	0.910	1.321	1.288	1.319	1.455	1.321	0.895	1.148	0.936
	102%	1.020	1.270	1.250	1.295	1.414	1.359	0.924	1.095	0.933
	105%	1.066	1.185	1.210	1.343	1.391	1.286	0.663	1.057	0.938
	110%	1.029	1.074	1.094	1.236	1.270	1.281	0.883	0.956	0.911
long call	90%	0.936	0.890	0.893	1.016	0.746	0.721	0.783	0.760	0.767
	95%	0.964	0.858	0.877	0.917	0.870	0.948	0.818	0.726	0.774
	100%	0.970	0.841	0.853	1.032	1.020	1.082	0.793	0.713	0.738
	102%	0.917	0.831	0.846	1.043	1.025	1.094	0.760	0.719	0.772
	105%	0.906	0.849	0.845	1.061	1.052	1.010	0.790	0.728	0.769
	110%	0.945	0.904	0.890	1.138	1.085	1.101	0.824	0.759	0.782
short put	90%	0.975	1.155	1.149	1.150	1.296	1.291	0.888	0.988	1.011
	95%	0.975	1.168	1.166	1.317	1.353	1.328	0.912	0.972	1.014
	100%	1.017	1.181	1.168	1.190	1.404	1.388	1.089	1.017	1.048
	102%	1.080	1.189	1.170	1.333	1.356	1.390	1.080	0.996	0.874
	105%	1.088	1.162	1.157	1.577	1.632	1.501	1.054	0.944	1.028
	110%	1.038	1.128	1.124	1.093	1.205	1.333	1.119	0.940	1.000
long put	90%	1.018	0.819	0.810	1.113	1.069	1.044	0.816	0.721	0.674
	95%	1.051	0.775	0.768	1.095	1.012	0.985	0.750	0.676	0.635
	100%	1.022	0.663	0.692	0.832	0.826	1.020	0.615	0.517	0.490
	102%	0.886	0.582	0.641	0.841	0.750	0.811	0.619	0.481	0.427
	105%	0.813	0.511	0.567	0.473	0.337	0.492	0.503	0.444	0.336
	110%	0.945	0.501	0.582	0.844	0.693	0.405	0.495	0.392	0.255
short straddle	90%	0.820	2.233	1.734	0.925	1.745	1.866	0.761	1.183	1.089
	95%	0.813	1.595	1.480	1.433	1.696	1.578	0.851	1.053	1.036
	100%	0.935	1.383	1.346	1.234	1.549	1.459	1.123	1.172	1.109
	102%	1.087	1.349	1.317	1.383	1.451	1.472	1.130	1.108	0.866
	105%	1.125	1.265	1.275	1.684	1.784	1.565	0.873	1.022	1.069
	110%	1.059	1.171	1.174	1.106	1.223	1.355	1.130	0.981	1.021
long straddle	90%	0.948	0.804	0.798	0.966	0.676	0.620	0.756	0.689	0.667
	95%	0.994	0.739	0.751	0.852	0.753	0.805	0.749	0.625	0.642
	100%	0.979	0.637	0.662	0.770	0.779	0.942	0.597	0.501	0.500
	102%	0.806	0.555	0.608	0.747	0.709	0.833	0.541	0.461	0.487
	105%	0.696	0.463	0.524	0.446	0.422	0.494	0.462	0.388	0.400
	110%	0.852	0.369	0.483	0.803	0.627	0.428	0.459	0.302	0.279
short strangle	ATM +- 5%	1.028	1.340	1.348	1.445	1.497	1.382	0.722	1.116	1.079
	ATM +- 10%	1.010	1.243	1.250	1.173	1.351	1.349	0.903	1.077	1.060
long strangle	ATM +- 5%	0.941	0.674	0.671	0.959	0.890	0.828	0.687	0.576	0.592
	ATM +- 10%	0.969	0.749	0.732	1.046	0.958	0.952	0.777	0.634	0.619
short butterfly	ATM +- 5%	0.862	0.789	0.818	0.950	0.983	1.010	0.492	0.559	0.553
	ATM +- 10%	0.834	0.702	0.733	0.748	0.937	1.185	0.576	0.475	0.515
long butterfly	ATM +- 5%	0.748	0.874	0.850	0.801	0.684	0.640	0.720	0.659	0.629
	ATM +- 10%	0.764	1.011	0.959	1.021	0.554	0.434	0.742	0.784	0.660
short put spread	short put 5% OTM	0.929	0.949	0.885	0.752	1.150	0.960	1.234	0.744	0.783
	short put 10% OTM	1.022	1.057	1.045	1.118	1.307	1.277	1.042	0.910	0.907
long put spread	long put 5% OTM	0.918	0.866	0.858	0.378	0.522	0.706	0.620	0.802	0.698
	long put 10% OTM	0.934	0.970	1.004	0.960	1.070	1.212	0.668	0.713	0.747
short put call spread	short put 5% OTM	0.978	1.029	0.989	1.186	1.216	0.870	0.751	0.878	0.453
	short put 10% OTM	0.942	1.027	1.000	1.198	1.255	1.031	0.831	0.901	0.580
long put call spread	long put 5% OTM	0.967	0.956	0.973	0.998	1.094	1.157	0.811	0.794	0.846
	long put 10% OTM	0.970	0.984	1.000	1.121	1.153	1.196	0.836	0.805	0.864

Table 6 Factor Risk-Adjusted Performance using Leland's alpha

This table shows Leland`s (1999) alphas and p-values (bootstrapped using 1,000 simulations) for regressions of monthly option strategy excess returns on underlying index excess returns. The period covered is from January 2006 to September 2010.

		Panel A: S&P 500						*Panel B: DAX*						*Panel C: EURO STOXX 50*					
		1 Month		2 Months		3 Months		1 Month		2 Months		3 Months		1 Month		2 Months		3 Months	
Strategy	Strike	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p	α_{Leland}	p
short call	90%	-0.0010	0.24	0.0027	0.38	0.0024	0.38	-0.0020	0.83	0.0051	0.00	0.0075	0.00	-0.0029	0.17	0.0002	0.61	-0.0004	0.34
	95%	-0.0016	0.18	0.0029	0.37	0.0026	0.36	0.0023	0.01	0.0043	0.00	0.0030	0.01	-0.0015	0.28	0.0012	0.56	-0.0002	0.36
	100%	-0.0013	0.20	0.0034	0.31	0.0029	0.34	0.0019	0.01	0.0026	0.01	0.0011	0.02	0.0003	0.64	0.0035	0.36	0.0009	0.55
	102%	0.0005	0.61	0.0035	0.27	0.0030	0.34	0.0016	0.01	0.0027	0.01	0.0017	0.02	0.0010	0.54	0.0034	0.36	0.0010	0.56
	105%	0.0014	0.51	0.0030	0.33	0.0030	0.35	0.0025	0.01	0.0028	0.00	0.0011	0.04	-0.0069	0.05	0.0033	0.40	0.0012	0.56
	110%	0.0008	0.59	0.0015	0.51	0.0018	0.47	0.0006	0.03	0.0012	0.02	0.0013	0.03	0.0003	0.60	0.0019	0.50	0.0009	0.54
long call	90%	-0.0017	0.19	-0.0035	0.07	-0.0032	0.10	-0.0054	0.52	-0.0154	0.01	-0.0157	0.01	-0.0036	0.16	-0.0048	0.10	-0.0043	0.12
	95%	-0.0008	0.24	-0.0045	0.05	-0.0037	0.08	-0.0088	0.19	-0.0109	0.10	-0.0078	0.29	-0.0020	0.24	-0.0063	0.06	-0.0037	0.16
	100%	-0.0005	0.29	-0.0045	0.05	-0.0041	0.06	-0.0045	0.63	-0.0052	0.53	-0.0034	0.72	-0.0024	0.21	-0.0061	0.06	-0.0047	0.11
	102%	-0.0018	0.18	-0.0044	0.06	-0.0041	0.07	-0.0039	0.67	-0.0047	0.62	-0.0030	0.79	-0.0032	0.16	-0.0054	0.08	-0.0033	0.18
	105%	-0.0018	0.18	-0.0035	0.08	-0.0038	0.07	-0.0032	0.74	-0.0038	0.69	-0.0047	0.60	-0.0020	0.23	-0.0044	0.10	-0.0031	0.17
	110%	-0.0009	0.25	-0.0019	0.19	-0.0023	0.17	-0.0014	0.89	-0.0026	0.81	-0.0025	0.81	-0.0010	0.30	-0.0030	0.18	-0.0023	0.21
short put	90%	-0.0003	0.33	0.0034	0.29	0.0035	0.29	-0.0013	0.89	0.0017	0.02	0.0017	0.02	0.0006	0.60	0.0032	0.38	0.0039	0.33
	95%	-0.0003	0.30	0.0041	0.21	0.0043	0.19	0.0020	0.01	0.0032	0.01	0.0027	0.01	0.0013	0.51	0.0033	0.37	0.0045	0.32
	100%	0.0008	0.55	0.0052	0.14	0.0048	0.16	0.0000	0.94	0.0050	0.00	0.0045	0.00	0.0064	0.19	0.0050	0.28	0.0058	0.18
	102%	0.0027	0.34	0.0058	0.13	0.0051	0.15	0.0036	0.01	0.0043	0.00	0.0048	0.00	0.0066	0.20	0.0047	0.29	0.0006	0.60
	105%	0.0031	0.29	0.0054	0.14	0.0050	0.16	0.0087	0.00	0.0110	0.00	0.0077	0.00	0.0061	0.19	0.0030	0.40	0.0056	0.22
	110%	0.0016	0.51	0.0045	0.20	0.0042	0.25	-0.0028	0.76	0.0001	0.06	0.0038	0.01	0.0079	0.12	0.0030	0.40	0.0048	0.27
long put	90%	0.0005	0.63	-0.0033	0.09	-0.0031	0.10	-0.0016	0.87	-0.0022	0.83	-0.0024	0.82	-0.0013	0.29	-0.0035	0.15	-0.0044	0.10
	95%	0.0010	0.55	-0.0035	0.09	-0.0033	0.10	-0.0017	0.86	-0.0027	0.82	-0.0031	0.76	-0.0028	0.19	-0.0040	0.15	-0.0045	0.12
	100%	0.0003	0.64	-0.0037	0.08	-0.0033	0.10	-0.0063	0.44	-0.0046	0.61	-0.0017	0.86	-0.0057	0.08	-0.0054	0.08	-0.0060	0.06
	102%	-0.0014	0.22	-0.0037	0.07	-0.0033	0.08	-0.0052	0.53	-0.0049	0.60	-0.0042	0.61	-0.0053	0.09	-0.0048	0.10	-0.0062	0.05
	105%	-0.0021	0.16	-0.0029	0.10	-0.0030	0.10	-0.0142	0.02	-0.0118	0.04	-0.0085	0.22	-0.0078	0.03	-0.0047	0.09	-0.0065	0.07
	110%	-0.0004	0.30	-0.0013	0.23	-0.0015	0.18	-0.0053	0.52	-0.0075	0.31	-0.0126	0.04	-0.0077	0.03	-0.0056	0.08	-0.0063	0.06
short straddle	90%	-0.0019	0.18	0.0052	0.13	0.0047	0.19	-0.0035	0.72	0.0059	0.00	0.0081	0.00	-0.0026	0.17	0.0023	0.42	0.0023	0.43
	95%	-0.0028	0.11	0.0058	0.13	0.0055	0.11	0.0037	0.01	0.0062	0.00	0.0044	0.00	-0.0008	0.33	0.0031	0.41	0.0028	0.42
	100%	-0.0014	0.23	0.0074	0.05	0.0064	0.10	0.0012	0.03	0.0063	0.00	0.0042	0.00	0.0060	0.20	0.0071	0.14	0.0054	0.22
	102%	0.0025	0.40	0.0082	0.02	0.0068	0.07	0.0045	0.00	0.0058	0.00	0.0051	0.00	0.0069	0.17	0.0068	0.18	0.0002	0.61
	105%	0.0040	0.24	0.0074	0.05	0.0069	0.06	0.0108	0.00	0.0128	0.00	0.0077	0.00	-0.0008	0.29	0.0052	0.25	0.0058	0.23
	110%	0.0022	0.43	0.0056	0.14	0.0054	0.13	-0.0024	0.83	0.0008	0.03	0.0043	0.00	0.0082	0.11	0.0043	0.33	0.0051	0.27
long straddle	90%	-0.0013	0.21	-0.0064	0.01	-0.0060	0.02	-0.0067	0.37	-0.0172	0.00	-0.0176	0.00	-0.0047	0.09	-0.0078	0.03	-0.0082	0.03
	95%	0.0001	0.66	-0.0076	0.01	-0.0066	0.01	-0.0102	0.11	-0.0132	0.03	-0.0104	0.10	-0.0046	0.11	-0.0098	0.01	-0.0078	0.02
	100%	-0.0002	0.31	-0.0079	0.01	-0.0071	0.01	-0.0104	0.09	-0.0093	0.19	-0.0049	0.59	-0.0079	0.03	-0.0111	0.01	-0.0103	0.01
	102%	-0.0031	0.10	-0.0078	0.00	-0.0070	0.01	-0.0089	0.21	-0.0093	0.18	-0.0069	0.36	-0.0083	0.02	-0.0098	0.01	-0.0091	0.01
	105%	-0.0039	0.07	-0.0062	0.02	-0.0065	0.02	-0.0170	0.00	-0.0152	0.01	-0.0126	0.03	-0.0096	0.01	-0.0088	0.02	-0.0093	0.02
	110%	-0.0013	0.24	-0.0030	0.12	-0.0035	0.08	-0.0065	0.40	-0.0099	0.13	-0.0147	0.01	-0.0086	0.02	-0.0083	0.02	-0.0084	0.03

Table 6 (continued)

		Panel A: S&P 500						Panel B: DAX						Panel C: EURO STOXX 50					
		1 Month		2 Months		3 Months		1 Month		2 Months		3 Months		1 Month		2 Months		3 Months	
Strategy	Strike	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*	α_{Leland}	*p*
short strangle	ATM+-5%	0.0008	0.57	0.0067	0.09	0.0067	0.06	0.0044	0.00	0.0056	0.00	0.0032	0.01	-0.0056	0.07	0.0062	0.20	0.0050	0.26
	ATM+-10%	0.0004	0.63	0.0049	0.17	0.0051	0.17	-0.0007	0.92	0.0028	0.01	0.0027	0.01	0.0009	0.59	0.0049	0.29	0.0046	0.30
long strangle	ATM+-5%	-0.0009	0.25	-0.0068	0.01	-0.0069	0.01	-0.0047	0.59	-0.0063	0.43	-0.0075	0.32	-0.0047	0.11	-0.0082	0.03	-0.0074	0.04
	ATM+-10%	-0.0004	0.30	-0.0051	0.04	-0.0053	0.04	-0.0030	0.79	-0.0047	0.60	-0.0048	0.58	-0.0023	0.20	-0.0064	0.05	-0.0066	0.05
short butterfly	ATM+-5%	-0.0023	0.13	-0.0038	0.06	-0.0032	0.09	-0.0050	0.58	-0.0043	0.64	-0.0035	0.72	-0.0135	0.00	-0.0085	0.02	-0.0083	0.04
	ATM+-10%	-0.0030	0.11	-0.0066	0.02	-0.0059	0.02	-0.0123	0.03	-0.0063	0.44	0.0001	0.06	-0.0091	0.02	-0.0130	0.00	-0.0111	0.00
long butterfly	ATM+-5%	-0.0055	0.03	-0.0022	0.15	-0.0026	0.15	-0.0087	0.21	-0.0102	0.10	-0.0103	0.10	-0.0040	0.13	-0.0049	0.09	-0.0056	0.07
	ATM+-10%	-0.0052	0.04	0.0004	0.62	-0.0005	0.30	-0.0032	0.76	-0.0125	0.03	-0.0149	0.01	-0.0042	0.13	-0.0019	0.23	-0.0051	0.08
short put spread	long put 5% OTM	-0.0005	0.30	-0.0002	0.31	-0.0004	0.31	-0.0033	0.74	0.0000	0.95	-0.0007	0.91	0.0021	0.46	-0.0011	0.30	-0.0006	0.33
	long put 10% OTM	0.0009	0.56	0.0017	0.50	0.0013	0.52	-0.0018	0.87	0.0025	0.01	0.0016	0.02	0.0049	0.28	0.0013	0.53	0.0011	0.54
long put spread	short put 5% OTM	-0.0009	0.23	-0.0013	0.21	-0.0010	0.25	-0.0080	0.27	-0.0040	0.67	-0.0015	0.88	-0.0056	0.06	-0.0031	0.17	-0.0031	0.19
	short put 10% OTM	-0.0008	0.24	-0.0003	0.31	0.0002	0.63	-0.0045	0.63	-0.0022	0.85	0.0000	0.05	-0.0048	0.08	-0.0029	0.19	-0.0023	0.23
short put call spread	long put 5% OTM	-0.0002	0.34	0.0002	0.65	0.0000	0.35	0.0003	0.05	0.0002	0.05	-0.0015	0.88	-0.0025	0.22	-0.0002	0.39	-0.0030	0.16
	long put 10% OTM	-0.0007	0.27	0.0003	0.62	0.0001	0.67	0.0003	0.05	0.0006	0.04	-0.0010	0.91	-0.0010	0.31	0.0002	0.64	-0.0031	0.18
long put call spread	short put 5% OTM	-0.0006	0.26	-0.0010	0.27	-0.0005	0.29	-0.0057	0.50	-0.0034	0.74	-0.0016	0.87	-0.0018	0.26	-0.0029	0.18	-0.0007	0.30
	short put 10% OTM	-0.0005	0.29	-0.0002	0.34	0.0003	0.64	-0.0024	0.81	-0.0018	0.86	-0.0004	0.93	-0.0009	0.30	-0.0025	0.21	0.0000	0.36

V. Article 4: Bond Mutual Funds and Complex Investments

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Abstract. This is the first paper to analyze bond mutual funds' permission and use of complex investments, such as derivatives, illiquid securities, and securities lending, employing a unique dataset of comprehensive regulatory information from the SEC's N-SAR filings. While most complex investments do not affect fund performance or risk characteristics, using interest rate futures is harmful for bond funds. Bond mutual funds engaging in interest rate futures (45.8% of all bond funds) underperform their non-using peers by a risk-adjusted return of 51 basis point per year. The results reveal that bond mutual funds employ interest rate futures for speculation as they increase their duration and thus their exposure towards interest rate risk.

JEL Classification: G11, G12

Keywords: Mutual fund performance; bond funds; performance; derivatives; interest rate futures

1. Introduction and literature overview

In 2014, the total assets under management of domestic bond funds in the US was $2,158 billion, a substantial growth from $831 billion a decade earlier.[1] Consequentially, there is an increasing amount of academic research on bond mutual funds starting with the seminal paper of Blake et al. (1993). Similar to Blake et al. (1993), most studies, such as Elton et al. (1995), Ferson et al. (2006), as well as Huij and Derwall (2008) among others, analyze bond fund performance and generally find that bond funds underperform their benchmarks. Although of great importance to both regulators and investors, the question of how bond funds actually invest has not garnered much academic attention. Only Cici and Gibson (2012) as well as Huang and Wang (2014) use security-level holdings data to analyze bond funds' picking and timing skills. Next to investing directly into bonds, mutual bond funds are also able to use complex investments, such as investing into derivatives, short selling bonds, obtaining leverage, and loaning out securities to increase performance or alter risk characteristics. Furthermore, the SEC examination priorities for 2016 are concerned with analyzing mutual fund complex investments, such as derivatives. Therefore, how and to what effects bond mutual funds employ complex investments is an important question.[2]

So far, research has mainly focused on equity mutual funds' use of complex investments. Almazan et al. (2004) examine complex investment restrictions for equity mutual funds. 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. A large literature stream focuses on equity funds' derivatives use. Lynch-Koski and Pontiff (1999), Frino et al. (2009), Cao et al. (2011), Cici and Palacios (2015), as well as Natter et al. (2016), and Rohleder et al. (2015) analyze how

[1] See Table 4 of Investment Company Institute Fact Book, 2015.

[2] See http://www.sec.gov/news/pressrelease/2016-4.html (accessed: 01/28/2016).

the use of derivatives affects equity mutual fund performance and risk characteristics with different results. Chen et al. (2013) find that short selling acts as a skill proxy for equity funds. In a recent working paper, Evans et al. (2015) relate equity funds lending of securities to their performance and find that lenders underperform non-lenders.

Complex investments may influence bond funds differently than equity funds. However, they have only been analyzed by Deli and Varma (2002) and by Adam and Guettler (2015). While the former find that transaction cost savings are the main drivers for the permission to invest in derivatives, the latter 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.

Closing this gap, we use a unique dataset containing regulatory information on complex investment permissions and usage for 1,059 actively managed U.S. domestic bond funds during the period 1999-2014 to show that bond funds frequently use complex investments. The data used in this paper is obtained from individual N-SAR filings downloaded from the SEC's EDGAR database and merged with fund returns and characteristics from the CRSP Survivor-Bias-Free Mutual Fund Database. Extending the literature on complex investments' impact on fund performance and risk characteristics to bond mutual funds, we show that overall complex investment permissions and engagement do not have significant performance impact. Funds' use of interest rate futures (IRF), however, negatively affects fund performance, leading to underperformance of IRF users by around 60 basis points per year. As 45.8% 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 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. Section 2 describes the data and performance measurement methodology. Section 3 describes the main empirical results while Section 4 presents alternative explanations and further tests. Section 5 concludes.

2. Data and methodology

2.1. Sample construction

One reason for the lack of research on bond funds' complex investments is that data on complex investments is 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 actual use of investment practices in semiannual N-SAR filings with the SEC.[3,4] Although several studies use N-SAR filings for the analysis of equity mutual funds, their use in bond fund analysis is rare.[5] Hence, our unique dataset stems from the CRSP Survivor-Bias-Free Mutual Fund Database and from mutual fund regulatory N-SAR filings with the SEC.

We select all funds with a CRSP objective indicating general, corporate, or government bond funds, i.e. funds with CRSP objective code equal to "I" or starting with

[3] For a detailed description of mutual fund complex investment regulation, see Chen et al. (2013) and Rohleder et al. (2015).

[4] 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 underestimates 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.

[5] Only Deli and Varma (2002) and Fulkerson et al. (2014) analyze N-SAR filings for bond funds.

"IC" and "IG", respectively.[6] 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 to 2014, as daily return data necessary for calculating time-varying performance and risk measures is only available in the CRSP database since September 1999.[7] Funds are only considered once they cross the threshold size of $5 million in TNA as in Fama and French (2010) and if they have at least 12 monthly observations.[8]

To obtain the final dataset, 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 to obtain data on fund characteristics and returns.[9] 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.[10] Furthermore, Table A1 in the 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 8,569 N-SAR filings with information of actively managed domestic bond funds available in CRSP.[11] This leads to a unique final dataset consisting of

[6] The results may be driven by differences between these fund types. Therefore, investment objective fixed effects are included in our regressions.

[7] 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.

[8] Results are robust to changing the respective levels to 15 million in TNA and 24 monthly observations.

[9] The EDGAR database is available at http://www.sec.gov/edgar.shtml.

[10] 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.

[11] One N-SAR filing may contain information on more than one individual fund.

1,059 individual bond funds with 14,102 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.

2.2. Variable definition

This paper takes 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 the respective complex investment 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.[12] 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, for the income category, 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

[12] 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.

complex investments, as the potential impact of complex investments on fund characteristics should be easier to detect for heavy users than for light users.

Data on fund characteristics and returns are 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. We calculate net flows as the difference of investor purchases and redemptions from a fund's N-SAR filings.[13] Manager tenure is the time the longest tenured manager has spent in the fund. We identify funds as retail (institutional) funds if at least 50% of TNA is in share classes targeted at retail (institutional) investors.

2.3. 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. Hence, performance and risk are calculated for each semiannual fund reporting period based on daily returns. Gross returns are used as they represent returns generated by bond fund investment decisions and thus better capture the behavior of fund managers.[14] 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):

$$er_{i,d,t} = \alpha_{i,t}^{4-f} + \beta_{TERM,i,t}\, TERM_{d,t} + \beta_{DEF,i,t}\, DEF_{d,t} \qquad (1)$$

$$+\beta_{opt,i,t}\, OPT_{d,t} + \beta_{mkt,i,t}\, MKTRF_{d,t} + \varepsilon_{i,d,t}.$$ [15,16]

[13] Item 28 of a fund's N-SAR filing.

[14] In addition, **Table** Table 6 also shows results for net returns.

[15] At least 60 daily observations are required for each semiannual reporting period.

Here, $er_{i,d,t}$ is fund i's daily gross fund returns in excess of the 1-month US T-Bill rate and $\alpha_{i,t}^{4-f}$ is fund i's risk-adjusted performance during quarter t. $TERM_{d,t}$ is the return difference between the Barclays Capital Intermediate Government and the 1-month US T-Bill rate and captures returns generated by increasing duration, i.e. higher interest rate risk.[17] The default factor ($DEF_{d,t}$) is the return difference of the Barclays Capital US High Yield and US Intermediate Government indices and captures returns generated by taking on higher default risk. The option factor $OPT_{d,t}$ captures nonlinearities due to investment in mortgage backed securities and is measured by the return difference of the of the Barclays Capital US Mortgage Backed Securities and US Intermediate Government indices. To control for possible equity exposure of bond funds (Comer and Rodriguez, 2013), $MKTRF_{d,t}$ measures the excess return of the CRSP value-weighted market index.[18]

3. Empirical analysis of complex investments

3.1. Descriptive statistics

Table 1 shows descriptive statistics. The average (median) bond fund has \$1,002 million (\$223 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 average 11.0 years old and managed by managers with an average tenure of 6.4 years. Turnover, as measured by the annual average turnover ratio of 152.40%, is higher than in studies of equity funds due to rebalancing of portfolios when bonds mature.

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[16] Non-synchronous trading in daily returns may bias the results. Therefore, in unreported analyses, Dimson's (1979) approach with regressors lagged and forwarded by one day is employed. The results, which are available upon request, are qualitatively the same.

[17] Returns on the Barclays bond indices are taken from Datastream.

[18] 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.

[Insert Table 1 here.]

Nearly two thirds of the sample bond funds (62.23%) charge loads to their customers upon buying or selling fund shares and half of all funds (52.41%) mainly cater to retail investors. Average yearly expense ratios of 0.82% 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 (4.77% on average). Over the course of the sample period, bond funds experience an average monthly net flow of nearly 1.55% documenting the growth of the bond fund market over the past 15 years. While mean excess gross and net returns are positive (0.30% and 0.23% per month), average gross alphas are positive (0.53% per year) and net of fee alphas are negative (−0.26% per year) in line with the existing literature, e.g. Elton et al. (1995), Huij and Derwall (2008), Cici and Gibson (2012). The TERM beta is positive on average with a mean of 0.2978 and median of 0.3142 implying that bond funds generate returns by earning term premia. The DEF beta is also positive with a mean (median) of 0.2355 (0.1460) indicating that bond funds also generate returns with spread strategies. The bond funds in our sample do not take on substantial mortgage or equity exposure as the exposures to the other factors are close to zero. The exposure to the term and default factor vary substantially between funds, as indicated by the high standard deviations of these factors (18.94% and 27.44%, respectively).

3.2. Complex investment permission and use

Complex investments may play a negligible role in the bond fund market since investors often seek bond funds as conservative investments whereas complex investments may be risky. On the other hand, bond funds may seek non-standard yield opportunities. Especially, in the highly competitive environment of the mutual fund industry, complex investments may be used by funds to distinguish themselves from their competitors. To get a first impression of bond funds' complex investments, Table 2 displays permission and use of non-standard investment practices. The majority of bond funds is permitted to use derivatives, invest in restricted securities, obtain leverage by borrowing money, or to use income generating strategies, such as security lending and repos.

[Insert Table 2 here.]

However, not all funds with permission to employ complex investments make use of this opportunity. For example, although 92.16% of all funds have the permission to use derivatives, only 48.63% actually engage in these instruments at least once over the sample period. Bond funds mainly use interest rate futures as nearly half of the sample funds (45.80%) employ them at least once. Options on bonds (19.74%) and futures (21.25%) are less common. Nevertheless, they are also used by a fifth of all funds.

By borrowing money in excess of 5% of their TNA, 25.97% 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 68.27% of all sample funds and 13.98% use this opportunity during the sample period, compared to 11.12% short sale users found 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 (74.41%) implying at least partially illiquid holdings. Nearly all funds (98.96%) have the permission to engage in repos and 63.74% of sample funds make use of this permission. Half of the funds employ securities lending (45.61%), in line with findings of Evans et al. (2015) for equity funds.

Panel B shows the percentage of time funds have permission to use (use) these complex investments. Similar to the findings for equity 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 (57.41%) of all fund-months. All other complex investments are used more sporadically. This implies tactical decision making by bond funds with respect to their complex investments. The usage changes further support this notion as bond funds engagement changes between 7% and 14% of the time. Permissions meanwhile do not change considerably. These descriptive statistics thus show that complex investments are an important aspect of bond fund investment behavior.

3.3. Determinants of complex investment practice permission and use

According to statistics presented in Table 2, bond mutual funds' investment permissions and engagement in complex investments vary between funds. Therefore, this section analyzes the drivers behind this finding. The possible determinants are 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.

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), information on individual bond fund permissions (use) is therefore combined into one permission (engagement) score. In the spirit of Almazan et al. (2004), the permission (engagement) score is computed by calculating the average of permission (engagement) dummies in each broad complex investment category derivatives, leverage, illiquid assets, and income.

Table 3 shows the marginal effects of a pooled tobit regression where the dependent variable is either a fund's permission score or its engagement score and all continuous 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 0.0182. The same is true for funds belonging to larger families (coefficient of 0.0545). 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 options by Lynch-Koski and Pontiff (1999) and Cici and Palacios (2015).

As in Deli and Varma (2002), bond funds' permission to invest into debt derivatives is positively related to their turnover (coefficient of 0.0144). 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 0.0151, implying that the infrastructure necessary to use complex investments, such as sophisticated risk management systems, back office personnel, and fund managers, is costly

In comparison to general and corporate bond funds, government bond funds are more restricted, possibly due to the fact that these funds attract especially risk averse investors.

[Insert Table 3 here.]

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. (2015) and securities lending in Evans et al. (2015). For corporate bond funds, Adam and Guettler (2015) also find that belonging to a large family severely increases the likelihood to use CDS. Cash is 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., 2015). Lagged fund performance affects neither complex investment permission nor engagement score.

3.3. Complex investments and fund performance

So far, this paper has 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. While Almazan et al. (2004) and Clifford et al. (2014) find no relation between complex investment restrictions and fund performance. Concerning equity funds' use of 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. Frino et al. (2009) and Rohleder et al. (2015) 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 non-users, both in long and short portfolios. Security lending or repurchase agreements may be employed as an additional income source. However, Evans et al. (2015) find that equity funds lending securities underperform their non-lending peers. Regarding bond funds, Adam and Guettler (2015) are the only ones to analyze non-standard investments in the form of CDS for the largest 100 U.S. 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 portfolio long in funds with permission (engagement) scores above the median score and short in funds with permission (engagement) scores below the median during the lagged reporting period.[19] Bond mutual funds with complex investment

[19] In unreported results, portfolios are formed based on engagement scores in the highest and lowest third of all scores. Results remain the same.

permissions above the median do not differ from those funds with less permission regarding their performance as (risk-adjusted) gross returns of the differential portfolio are indistinguishable from zero and switch signs depending on the performance measure used.

As Table 2 shows, permissions are often unbinding. Hence, it is not surprising that the mere permission to engage in complex investments does not alter fund performance. Turning to the actual use, overall engagement scores above the median also do not significantly influence performance. However, yearly risk-adjusted performance is negative across all performance measures. Thus, complex investment permission and engagement is not significantly related to bond fund performance similar to findings of Almazan et al. (2004).

[Insert Table 4 here.]

Aggregated scores may hide the effect of individual complex investments. Thus, Panel B of Table 4 analyzes the individual components of the complex investment engagement score. As one would expect from the results of Panel A, most complex investments' performance impact is indistinguishable from zero. Using interest rate futures (IRF), however, leads to significantly negative performance of the differential portfolio. Bond funds engaging in IRF underperform bond funds without engagement in IRF by 51 basis points on a yearly basis when we measure performance with the 4-factor model of 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 do not proxy for fund manager skill as it does for equity fund managers (Chen et al., 2013). Restricted securities also have no clear relation to fund performance. Income generating techniques, such as repos and lending of securities enhance gross returns, but do not offer any benefit on a risk-adjusted basis. However, they do not harm fund performance as shown for equity funds by Evans et al. (2015).

3.4. 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 pooled panel regression model:

$$Performance_{i,t} = \varphi_0 + \varphi_1 IRF_{i,t\text{-}1} + \sum_{j=2}^{J} \varphi_j \, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \qquad (2)$$

Here, $Performance_{i,t}$ is fund i's risk-adjusted annualized performance in semiannual reporting period t measured with the 4-factor model defined by Equation (1) in Section 2.3 and calculated using daily gross returns. $IRF_{i,t\text{-}1}$ is a dummy equal to one if fund i uses interest rate futures during reporting period t-1.[20,21] $Controls_{i,j,t\text{-}1}$ are the fund characteristics of Table 1 commonly associated with performance in the fund performance literature (e.g. Ferreira et al., 2012). Following Petersen (2009), standard errors are clustered by both fund and reporting period to control for heteroscedasticity and time-series as well as cross-sectional correlation.

[Insert Table 5 here.]

The results are displayed by Table 5. Column (1) shows a negative impact of engagement in IRF in reporting period t-1 on risk-adjusted fund performance in t. The coefficient of −63 basis points is economically substantial and significantly different from zero with a t-value of −4.38. This indicates that funds investing in IRF underperform otherwise similar funds.

When including control variables, the coefficient on IRF becomes −57 basis points (t-value of −4.03). The control variables are in line with the existing literature. Fund size has a

[20] In unreported analyses, using contemporaneous right hand side variables does not affect the results.

[21] In unreported analyses, regression (3) is carried out only for funds with permission to use IRF in order to circumvent 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.

positive impact on performance overall, but a negative relation within a fund, implying diseconomies of scale (Chen et al., 2004). Surprisingly, expense ratios have a positive relation to fund performance in contrast to existing studies for equity funds (e.g. Carhart, 1997). 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 fixed effects for different investment styles and fund fixed effects.[22] The negative relation between IRF engagement and performance holds. Coefficients are −0.0051 (t-value −3.67) and −0.0032 (−1.85) and imply a relevant economic magnitude of IRF users' underperformance. This indicates that bond funds do not profit from potential benefits of futures use, such as transaction cost savings, but rather face losses.

The origin of these losses, however, is not directly clear. 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.[23] 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

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[22] Results are also robust to the inclusion of family fixed effects.

[23] For example, in the prospectus for the T. Rowe Price U.S. Treasury funds, it states that 'The fund may use derivatives to adjust its sensitivity to interest rate changes'. See http://individual.troweprice.com/public/Retail/Mutual-Funds/hProspectuses&Reports/Prospectuses-&-Reports for details.

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, this beta should be amplified and IRF would be used to increase bond fund duration.

Panel B of Table 5 measures the relation between time varying interest rate (bond price) risk and IRF engagement in the following pooled panel regression:

$$\beta_{TERM,i,t} = \varphi_0 + \varphi_1 IRF_{i,t\text{-}1} + \sum_{j=2}^{J} \varphi_j \, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \tag{3}$$

$\beta_{TERM,i,t}$ is fund i's interest rate exposure in semiannual reporting period t measured with the 4-factor model defined in Equation (1) in Section 2.3 and calculated using daily gross returns.[24] $IRF_{i,t\text{-}1}$ and $Controls_{i,j,t\text{-}1}$ are defined as in Equation (2). Standard errors are clustered by both fund and reporting period following Petersen (2009).

Column (5) shows a positive coefficient of the IRF dummy. The coefficient of 0.0670 (t-value 4.86) implies that bond mutual funds engaging in IRF increase their term risk exposure by nearly 7%. When including control variables, this coefficient changes to 0.0417, still economically substantial and significantly different from zero with a t-value of 3.38. Consequently, bond funds do not use IRF to hedge against interest rate changes. Rather, they employ IRF to speculate on changes in interest rates as they use IRF to increase their portfolio duration. The result of a significant risk impact also holds for the fixed effects specifications in columns (7) and (8) and thus is not driven by omitted variables or cross-correlations in the data. Hence, IRF adversely affect fund performance and interest rate risk as bond funds employ them for speculative purposes.

[24] Additionally, we use the slope coefficient from a regression of fund gross excess returns on changes in the term spread, defined as the 10 year treasury yield minus the 1 year treasury yield as a dependent variable in regression (3). Results, not reported for brevity, are robust to this proxy.

4. Alternative explanations and further tests

4.1. Fees, using decisions and endogeneity

So far our results are based on gross of fee returns. To analyze whether the underperformance of IRF users also translates to lower returns for bond fund investors, the net returns panel of Table 6 shows results for net of fee returns. The coefficient of the IRF dummy is −55 basis points (0.0339) with a t-value of −3.96 (2.97) for fund performance (term risk). This indicates that the underperformance of bond funds using IRF is passed on to fund investors.

[Insert Table 6 here.]

The results so far do 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):

$$Performance_{i,t} = \varphi_0 + \varphi_1 IRF_{i,t\text{-}1} + \varphi_2 NONUSING_{i,t\text{-}1} + \sum_{j=3}^{J} \varphi_j\, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \quad (4)$$

$$Risk_{i,t} = \varphi_0 + \varphi_1 IRF_{i,t\text{-}1} + \varphi_2 NONUSING_{i,t\text{-}1} + \sum_{j=3}^{J} \varphi_j\, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \quad (5)$$

Here, $NONUSING_{i,t\text{-}1}$ is one if an IRF user fund does not use IRF in semiannual reporting period t-1 and zero otherwise. The user fund dummy is equal to one for all semiannual fund reporting periods after and including the first period a fund uses IRF. The non-using panel of Table 6 shows that the coefficients on IRF do not change substantially compared with the main specification 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 addition to results of Table 3, which show 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. To further alleviate any remaining concerns associated with endogeneity, the Endogeneity I panel of Table 6 include past performance, measured by the 4-factor alpha for reporting period t-1 from Equation (1) as an additional explanatory variable. Past performance has a positive impact on contemporaneous performance with a coefficient of 0.1322 (t-value 1.79) implying performance persistence among bond funds when controlling for fund characteristics (Huij and Derwall, 2008). The coefficient on IRF engagement is −47 basis points with a t-value of −3.38. This indicates that the possible endogenous relation between performance and IRF does not substantially influence the results. The last panel Table 6 (Endogeneity II) additionally include past interest rate risk, measured by $\beta_{TERM,i,t-1}$ from the 4-factor model, as funds may use derivatives in response to past risk exposures (Lynch-Koski, Pontiff, 1999). Past risk has no relation to fund performance and the results of a negative performance impact of IRF engagement still hold, with a coefficient of −52 basis points (t-value −3.79). 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.

4.2. Performance and risk models

The main analyses are only shown for performance and risk measured with the 4-factor model. However, in contrast to the literature on equity funds, where Carhart’s (1997) 4-factor model is the workhorse model to assess performance, no single 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:

$$er_{i,d,t} = \alpha_{i,t}^{M} + \sum_{k=1}^{K} \beta_{i,k,t}^{M}\, er_{k,d,t} + \varepsilon_{i,d,t}. \qquad (6)$$

Here, $\alpha_{i,t}^{M}$ represents fund *i*'s mean abnormal return measured with model *M*, while $er_{k,d,t}$ 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 as the only regressor in the single index model (SIM). The multi index model 2 (MIM-2) 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.

IRF may be used to alter returns 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:

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

where $\beta_{agg,i,t}^{Lel} = \frac{cov\left[R_{i,d,t} - \left(1+R_{agg,d,t}\right)^{-b}\right]}{cov\left[R_{agg,d},t - \left(1+R_{agg,d,t}\right)^{-b}\right]}$

with b $= \frac{ln\left[E\left(1+R_{agg,d,t}\right)\right] - ln\left(1+r_{f,d,t}\right)}{var\left[ln\left(1+R_{agg,d,t}\right)\right]}$

Here, $\alpha_{i,t}^{Lel}$ 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*, and $R_{agg,d,t}$ 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.

[Insert Table 7 here.]

Results in Panel A of Table 7 show robust findings across all performance measures. The coefficient on IRF dummy ranges from −133 basis points for Leland's alpha to −38 basis points for gross raw returns with t-values all below −2.90 indicating significance at conventional levels. Thus, performance results are not driven by model choice.

Panel B shows risk results for different models. Systematic exposure to bond price changes now does not solely encompass term risk, but also other risk drivers. Nevertheless, the betas are heavily impacted by IRF engagement as can be seen by the positive coefficients of the IRF dummy when explaining bond fund's single index beta (0.1440) or Leland's beta (0.1438). Both coefficients are significantly different from zero with t-values of 4.98. The aggregated beta factors from the MIM-1 and MIM-2 also capture bond price changes and are also positively affected by the IRF dummy, with coefficients of 0.0902 and 0.0812, respectively. Consequently, IRF users increase bond mutual funds systematic exposure to changes in bond prices and interest rates.

[Insert Table 8 here.]

Table 8 analyzes whether IRF usage also influences other bond fund risk characteristics. Fund return volatility and skewness are not affected by IRF engagement, with coefficients statistically not distinguishable from zero. Kurtosis is slightly lower for FCD users. Hence, bond funds engaging in IRF increase their interest rate risk by increasing their duration while decreasing idiosyncratic risk. The negative coefficient of −0.0424 (t-value of −7.02) on the default factor also shows that FCD user funds focus less on spread strategies by picking high yield bonds. This indicates that bond mutual funds employ IRF to make big bets on 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.

4.3. Propensity score matching analysis

To compare performance and risk of funds engaged in IRF with funds that do not use IRF, we employ a propensity score matching technique similar to Natter et al. (2016). In a first step, we use a probit regression of IRF engagement on lagged fund characteristics of Table 1 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.[25] 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. Table 9 reports results of these paired mean comparison tests.

[Insert Table 9 here.]

The gross performance difference between reporting periods in which funds are engaged in IRF and the control reporting periods presented in Panel A is −34 basis points and significant at the 1% level. The difference in term risk is an economically meaningful 0.0486, also significant at conventional levels. In Panel B, the probit regression for the calculation of the propensity score also includes a fund's lagged performance to control for possible endogeneity. The gross performance difference between IRF users and nonusers is still at −35 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 control funds by −26 basis points. This difference

[25] In unreported results, a one-to-one matching of using and non-using reporting periods is carried out. The results remain the same.

is significant at all conventional levels. Thus, our results can directly be attributed to the differential use of IRF.

4.4. Controlling for restriction and engagement score

Fund engagement in IRF may be correlated with the use of other complex investments. 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 in Section 3.2, but this time without incorporating the IRF dummy.

[Insert Table 10 here.]

Column (1) and (2) 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 −58 and −33 basis points, both significant with t-values of −4.22 and −1.91. 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, Panel B of Table 10 shows that fund complex investment permission and engagement score mostly have no influence on fund performance. Furthermore, the IRF coefficients remain positive and significantly different from zero. This implies that IRF are indeed the source of this paper's main results.

5. Conclusion

How bond mutual funds generate performance is of interest to academics, practitioners, and policy makers. 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 complex investments. Contributing to the literature on complex investments, which so far has mainly focused on equity funds, we show that there is no general relation between complex investment permission (use) and performance. However, investing into interest rate futueres, which is done by almost half of the funds and overall in almost a third of all reporting periods, severely harms bond fund performance as bond funds use these derivatives to speculate on interest rate changes by increasing their duration.

Overall, we help answer the question what kind of complex investments bond mutual funds use and how this affects performance and risk. Hence, investors should be careful when investing in bond mutual funds and take into account these complex investments.

Appendix: Merged N-SAR and CRSP fund sample

Table A1 displays averages of fund characteristics for both the merged N-SAR/CRSP sample and the complete actively managed domestic bond fund universe from CRSP. Funds in the merged sample have higher TNA and are somewhat older. Evans et al. (2015) and Rohleder et al. (2015) 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 U.S. domestic bond funds.

Table A1

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

	Panel A: NSAR matched data							Panel B: CRSP data						
Year	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	0.0085	1.4450	8.8	0.0067	0.0007	870	461	0.0089	1.4520	8.8	0.0065	0.0004
2000	456	449	0.0085	1.4890	9.1	-0.0153	0.0053	920	414	0.0089	1.3870	9.3	0.0451	0.0051
2001	470	439	0.0087	1.5650	9.6	0.0292	0.0052	927	463	0.0089	1.5090	9.7	0.0433	0.0052
2002	507	587	0.0088	1.6660	10.2	0.0249	0.0055	917	559	0.0089	1.6960	10.1	0.0586	0.0052
2003	526	702	0.0088	1.5900	10.6	0.0242	0.0067	920	682	0.0089	1.6610	10.5	0.0377	0.0062
2004	542	727	0.0085	1.6540	11.3	0.0043	0.0041	922	709	0.0087	1.7240	11.1	0.0053	0.0037
2005	669	894	0.0084	1.4940	11.9	0.0012	0.0021	926	742	0.0086	1.5340	11.4	0.0369	0.0018
2006	679	907	0.0082	1.3750	12.4	-0.0109	0.0041	895	805	0.0083	1.4440	12.2	0.0070	0.0042
2007	670	1,039	0.0080	1.4520	12.8	0.0322	0.0039	881	911	0.0081	1.4730	12.6	0.0221	0.0038
2008	648	1,113	0.0078	1.5220	13.6	0.0085	-0.0049	875	969	0.0080	1.5590	13.4	0.0089	-0.0058
2009	639	1,281	0.0077	1.5610	14.3	0.0268	0.0124	848	1,121	0.0079	1.6310	13.9	0.0287	0.0123
2010	628	1,732	0.0077	1.5390	14.7	0.0158	0.0063	844	1,501	0.0079	1.5960	14.3	0.0211	0.0063
2011	631	1,891	0.0076	1.5300	14.9	0.0161	0.0038	861	1,623	0.0078	1.6070	14.2	0.0557	0.0039
2012	671	2,092	0.0076	1.5500	15.2	0.0171	0.0059	874	1,815	0.0077	1.5950	14.2	0.1270	0.0059
2013	634	2,136	0.0076	1.3980	15.5	0.0053	0.0005	884	1,883	0.0076	1.4880	14.5	0.0087	0.0005
2014	466	1,893	0.0074	1.2840	16.4	0.0058	0.0038	833	1,961	0.0074	1.3680	15.7	0.0070	0.0028

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.

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Tables

Table 1
Summary statistics

	Mean	Median	Std. Dev.
Fund characteristics			
TNA ($mil)	1,002	223	5,445
Family TNA ($mil)	108,595	26,031	253,742
Age (Years)	11.0	9.1	8.2
Manager tenure	6.4	5.4	4.1
Turnover ratio (% TNA, p.a)	1.5240	0.9217	1.7813
Load dummy	0.6223	1.0000	0.4850
Retail fund dummy	0.5241	1.0000	0.4628
Expense ratio (% TNA, p.a)	0.0082	0.0078	0.0038
Cash (% TNA)	0.0477	0.0374	0.1461
Net flow (% TNA)	0.0155	0.0048	0.0906
Fund performance and risk			
Excess gross return	0.0030	0.0030	0.0032
Excess net return	0.0023	0.0023	0.0032
Volatility	0.0135	0.0110	0.0092
4-factor alpha (gross)	0.0005	0.0007	0.0023
4-factor alpha (net)	-0.0002	0.0001	0.0024
TERM beta	0.2978	0.3142	0.1894
DEF beta	0.2355	0.1460	0.2744
OPT beta	0.0043	0.0001	0.0189
MKT beta	0.0369	0.0168	0.0748

This table presents mean, median, and standard deviation of fund characteristics for 1,059 actively managed domestic bond funds with entries in N-SAR filings and the CRSP mutual fund database during the period 1999-2014. All variables are per month except where noted.

Table 2

Complex investment permission and use

	Panel A: Cross-section		Panel B: Semiannual			
	Permission	Use	Permission	Use	Permission changes	Usage changes
Derivatives	0.9216	0.4863	0.8884	0.3337	0.0093	0.0903
Bond options	0.8914	0.1974	0.8475	0.0685	0.0135	0.1259
Interest rate futures	0.8942	0.4580	0.8442	0.3094	0.0137	0.0896
Futures options	0.8857	0.2125	0.8426	0.1015	0.0143	0.1120
Leverage	0.9764	0.3513	0.9277	0.1220	0.1346	0.1346
Borrowing money	0.9528	0.2597	0.8779	0.0710	0.0172	0.1312
Margin purchases	0.3031	0.0142	0.1908	0.0035	0.0432	0.0781
Short selling	0.6827	0.1398	0.5189	0.0555	0.0345	0.1359
Restricted securities	0.9528	0.7441	0.9433	0.5741	0.0075	0.0758
Income	0.9934	0.7290	0.9916	0.6055	0.0647	0.0647
Repos	0.9896	0.6374	0.9860	0.4717	0.0032	0.0693
Security lending	0.9433	0.4561	0.9265	0.3051	0.0099	0.0876

This table shows descriptive statistics 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.

Table 3
Tobit regression of complex investment permission and engagement score

	Permission score	Engagement score
Log TNA	0.0182**	0.0558***
	(2.49)	(8.24)
Log family TNA	0.0545***	0.0555***
	(7.25)	(7.63)
Age	-0.0205***	0.0037
	(3.47)	(0.61)
Manager tenure	-0.0168***	-0.0122**
	(2.79)	(2.21)
Turnover ratio	0.0144***	0.0379***
	(3.57)	(4.97)
Load dummy	0.0239*	0.0200
	(1.80)	(1.53)
Retail dummy	-0.0248**	-0.0140
	(2.05)	(1.23)
Expense ratio	0.0151**	0.0078
	(2.57)	(1.26)
Cash	-0.0144***	-0.0170***
	(2.97)	(4.58)
Net flow	-0.0002	-0.0006
	(0.23)	(1.09)
Performance	0.0004	-0.0014
	(0.20)	(0.58)
Government	-0.0771***	-0.1560***
	(5.09)	(9.49)
Corporate	0.0141	-0.0179
	(0.91)	(1.13)
Time fixed effects	Yes	Yes
Cox-Snell R^2	0.199	0.274
N	14,102	14,102

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. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors clustered by fund are given in parentheses.

Table 4

Complex investment portfolio sorts

	Panel A: Complex investment scores		Panel B: Individual complex investments								
	Permission score	Engagement score	Bond options	Interest rate futures	Futures options	Borrowing money	Margin purchases	Short selling	Restricted securities	Repos	Security lending
Return	0.0036	-0.0046	0.0029	-0.0039	0.0030	0.0034	0.0008	-0.0014	0.0004	0.0029*	0.0041*
	(1.00)	(-0.71)	(0.92)	(-1.05)	(0.70)	(0.51)	(0.09)	(-0.36)	(0.12)	(1.75)	(1.84)
4-factor alpha	0.0014	-0.0016	-0.0009	-0.0051**	-0.0022	0.0014	-0.0071	-0.0023	-0.0014	0.0006	0.0021
	(0.98)	(-0.91)	(-0.32)	(-2.59)	(-0.80)	(0.89)	(-0.82)	(-0.79)	(-0.51)	(0.69)	(1.09)

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. ***, **, * denote 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.

Table 5
Performance and term risk regression

	Panel A: Performance				Panel B: Term beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IRF	-0.0063***	-0.0057***	-0.0051***	-0.0032*	0.0670***	0.0417***	0.0339***	0.0080*
	(-4.38)	(-4.03)	(-3.67)	(-1.85)	(4.86)	(3.38)	(2.97)	(1.87)
Log TNA		0.0006	0.0004	-0.0061***		0.0024	0.0038	0.0004
		(1.08)	(0.80)	(-5.28)		(0.57)	(1.01)	(0.15)
Log family TNA		0.0010**	0.0010**	-0.0007		0.0012	0.0048	0.0007
		(2.11)	(2.22)	(-0.57)		(0.40)	(1.54)	(0.26)
Age		-0.0002***	-0.0001**	-0.0001		0.0011	-0.0007	0.0011
		(-2.91)	(-2.36)	(-0.09)		(1.32)	(-0.94)	(0.70)
Manager tenure		0.0001	0.0000	-0.0001		-0.0023**	-0.0017*	-0.0010**
		(0.70)	(0.40)	(-0.97)		(-2.31)	(-1.91)	(-2.28)
Turnover ratio		-0.0002	-0.0001	0.0002		0.0116***	0.0105***	0.0003
		(-0.48)	(-0.33)	(0.60)		(3.99)	(3.46)	(0.34)
Load dummy		-0.0014	-0.0014			-0.0036	0.0007	
		(-0.97)	(-0.93)			(-0.25)	(0.06)	
Retail dummy		-0.0001	0.0001			0.0026	0.0044	
		(-0.11)	(0.10)			(0.19)	(0.33)	
Expense ratio		1.3040***	1.2323***	0.6019		-1.0122	0.0806	2.7824**
		(3.53)	(3.49)	(0.97)		(-0.48)	(0.04)	(2.33)
Cash		0.0136	0.0125	0.0192**		-0.1074	-0.0965	0.0445
		(1.50)	(1.32)	(2.06)		(-1.42)	(-1.38)	(1.10)
Net flow		-0.0000	-0.0000	-0.0000		0.0006***	0.0004**	0.0003***
		(-0.24)	(-0.20)	(-0.11)		(2.61)	(2.02)	(2.75)
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	0.39	0.40	0.40	0.43	0.08	0.11	0.21	0.87
N	14,102	14,102	14,102	14,102	14,102	14,102	14,102	14,102

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. All explanatory variables are lagged one reporting period. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

Table 6

Performance and term risk regression - Alternative explanations

	Net returns		Non-using		Endogeneity I		Endogeneity II	
	Performance	Term beta	Performance	Term beta	Performance	Term beta	Performance	Term beta
IRF	-0.0055***	0.0339***	-0.0053***	0.0351***	-0.0047***	0.0324***	-0.0052***	0.0077**
	(-3.96)	(2.97)	(-3.55)	(2.89)	(-3.38)	(2.84)	(-3.79)	(2.38)
Non-using			0.0013	0.0080				
			(0.66)	(0.58)				
Performance					0.1322*	-0.2434***		
					(1.79)	(-2.85)		
Risk							-0.0079	0.9897***
							(-1.45)	(25.44)
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	0.40	0.21	0.40	0.21	0.41	0.86	0.40	0.86
N	14,102	14,102	14,102	14,102	14,102	14,102	14,102	14,102

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, 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 is one if a user fund does not use interest rate futures in the respective semiannual reporting period and in all other cases zero. The user fund dummy is equal to one for all semiannual fund reporting periods after a fund first uses interest rate futures. All explanatory variables are lagged one reporting period. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

Table 7

Performance and term risk regression - Different performance models

	Panel A: Performance					Panel B: Term beta			
	Return	SIM	MIM-1	MIM-2	Leland	SIM	MIM-1	MIM-2	Leland
IRF	-0.0038***	-0.0118***	-0.0053***	-0.0054***	-0.0133***	0.1440***	0.0902***	0.0812***	0.1438***
	(-2.90)	(-4.99)	(-3.97)	(-4.23)	(-5.43)	(4.98)	(3.95)	(3.50)	(4.98)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.41	0.32	0.22	0.24	0.31	0.24	0.24	0.20	0.24
N	14,102	14,102	14,102	14,102	14,102	14,102	14,102	14,102	14,102

This table shows results of a pooled panel regression of fund performance (Panel A) and term 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. All explanatory variables are lagged one reporting period. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-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	0.0297	-0.2733*	-0.0424***	0.0396***	-0.0087***
	(-0.04)	(0.82)	(-1.67)	(-7.02)	(4.05)	(-3.39)
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. R2	0.31	0.19	0.06	0.38	0.27	0.10
N	14,102	14,102	14,102	14,102	14,102	14,102

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. All explanatory variables are lagged one reporting period. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and semiannual reporting period following Petersen (2009) are given in parentheses.

Table 9

Performance and term risk - Propensity score matching

	Performance		Term beta	
Panel A: All control variables				
Interest rate futures engaged	0.0112		0.2757	
Control group	0.0145		0.2272	
Difference	-0.0034	***	0.0486	***
Panel B: All control variables plus performance				
Interest rate futures engaged	0.0112		0.2757	
Control group	0.0147		0.2269	
Difference	-0.0035	***	0.0488	***
Panel C: All control variables plus performance & risk				
Interest rate futures engaged	0.0112		0.2757	
Control group	0.0138		0.2648	
Difference	-0.0026	***	0.0109	***

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, the matching is based on the fund characteristics used in Table 5. In Panel B, the 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. ***, **, * denote significance at the 1%, 5%, and 10% level, respectively.

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	-0.0058***	-0.0033*	-0.0064***	-0.0032*	0.0331***	0.0084**	0.0280**	0.0082**
	(-4.22)	(-1.91)	(-4.47)	(-1.86)	(2.92)	(1.98)	(2.40)	(1.99)
Permission	-0.0071**	-0.0059			-0.0165	0.0143		
	(-1.99)	(-0.81)			(-0.58)	(1.06)		
Engagement			0.0102***	0.0005			0.0621**	-0.0045
			(2.97)	(0.13)			(2.51)	(-0.38)
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	0.40	0.43	0.40	0.43	0.21	0.87	0.22	0.87
N	14,102	14,102	14,102	14,102	14,102	14,102	14,102	14,102

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. All explanatory variables are lagged one reporting period. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and semiannual reporting period are given following Petersen (2009) in parentheses.

VI. Article 5: International Mutual Funds and Foreign Currency Derivatives Use – Hedging or Speculation

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Abstract. This paper is the first to analyze how US based active international mutual funds employ foreign currency derivatives (FCD). Using fund holdings data from Morningstar to identify funds' derivative positions, the results show that more than half of all international funds employ FCD, which make up more than 5% of total holdings on average. Users of FCD hedge their foreign exchange exposure as they have lower international equity market risk than nonusers in periods when they heavily invest into FCD. Furthermore, they are less impacted by changes in exchange rates. However, this does not translate into benefits for investors, as risk-adjusted performance of FCD users is not superior to nonusers.

JEL Classification: G11, G15, G23

Keywords: Mutual fund performance, international funds, foreign currency derivatives, hedging

1. Introduction

US based international equity funds (IEF) offer international diversification benefits to fund investors. This appealing feature has led to high cumulative inflows into international equity funds over the last decade leading to total net assets under management in excess of 2,079 bn. as of 2014.[1] Thus, it is important to understand the specific feature of this investment segment compared to, e.g., domestic equity funds. Investing abroad makes international equity funds susceptible to changes in exchange rates. The appreciation or depreciation of foreign currencies versus the US dollar is reflected in fund's exposure towards foreign country indices. If international mutual funds use foreign currency derivatives (FCD) for speculation, they may increase their exchange rate risk beyond exchange rate movements inherent in foreign equity market indices and thus increase their systematic risk. On the other hand, funds may employ FCD to hedge their foreign exchange risk and thus decrease their exposure to foreign equity market indices. The strategy of international funds employing FCD is not clear a priori. For example, BlackRock states in its prospectus on its International Opportunities Portfolio that it 'typically uses derivatives as a substitute for taking a position in the underlying … or … to reduce exposure to other risks, such as currency risk. The Fund may also use derivatives to enhance returns'.[2] In this paper, I show that i) FCD engagement does not severely alter international mutual fund performance, ii) heavy FCD engagement is associated with lower exposure to the international market factor, and iii) international mutual funds employ FCD to hedge their exposure to international equity markets.

Thereby, I contribute to the literature on internationally and globally investing funds by being the first to investigate their FCD positions. Despite the increasing importance of the

[1] See Table 4 of Investment Company Institute Fact Book, 2015.

[2] See https://www.blackrock.com/investing/products/227462/blackrock-international-opportunitiesinst-cl-fund for details.

fund class for US investors, research on international funds is still sparse. Detzler and Wiggins (1997), Busse et al. (2014) as well as Breloer et al. (2014) find no outperformance of global and international funds compared to standard benchmark models. Gallagher and Jarnecic (2004) show similar results for international Australian equity funds. Gallo and Swanson (1996) and Huij and Derwall (2011) meanwhile find outperformance of international funds in comparison to their benchmarks. Only Hiraki et al. (2015) analyze in more detail how international funds invest by looking at their stock holdings. However, they do not consider fund's FCD holdings.

Moreover, I contribute to the literature on FCD, which so far has focused on how banks (Choi, 1997) and nonfinancials (Allayannis and Weston, 2001; Allayannis and Ofek, 2001; Bartram et al., 2011) employ FCD. Their results indicate that companies use FCD to lower their risk and increase their firm value. However, currency speculation is not the core business of nonfinancial companies. For international mutual funds on the other hand, finding relative value, e.g., via FCD, in the international market is of paramount importance. Hence, analyzing how FCD affect fund performance and risk is an important question for investors, researchers, and regulators as documented by the new rules to govern mutual funds' derivative use proposed by the SEC.[3]

To address this question, I use holdings data from Morningstar which shows that US based international equity mutual funds (IEF) invest in a variety of foreign currencies. The Euro (EUR), Japanese Yen (JPY), and British Pound (GBP) are the most important currencies, as they make up 19.17%, 13.62%, and 12.72% of the average portfolio holdings, respectively. More than half (55.26%) of all international equity funds use FCD. Currency forwards are used at least once during the sample period by 52.83%. The use of currency futures (20.24%), options (3.85%), and swaps (0.61%) is less popular.

[3] See https://www.sec.gov/news/pressrelease/2015-276.html (accessed: 02/25/2016).

User funds are not constantly engaged in FCD as they employ them in only 18.04% of all fund-quarters. In case of use, they make up a substantial fraction (5.48%) of a fund's total holdings. EUR, JPY, and GBP are the most popular underlying currencies of FCD. This is a first indication that IEF use FCD to concentrate on existing portfolio currencies and do not broadly diversify their currency portfolio. To support this finding, I regress FCD use (FCD weight changes) on foreign currency holdings (change in foreign currency holdings). The results document that an increase in non-US holdings leads to an increased probability that a fund uses FCD (increases its weight in FCD).

To analyze if IEF use FCD to speculate on currency movements or to hedge against foreign exchange risk, I construct equal- and value-weighted portfolios long in IEF using FCD and short in IEF refraining from FCD use. This long-short FCD user portfolio has a statistically negative exposure to the international equity market factor, measured via the international CAPM and the international version of Fama and French's (1993) 3-factor model. This implies that funds use FCDs to lower their exposure to foreign currencies and markets. The equal-weighted long-short FCD user portfolio has significantly negative (risk-adjusted) performance whereas performance is indistinguishable from zero when looking at the value-weighted long-short FCD user portfolio. This suggests a size effect inherent in IEF performance. To control for size as well as other fund characteristics, I employ a panel regression to analyze the impact of FCD engagement on international fund performance and risk. While performance is unaffected by overall FCD engagement, funds heavily invested in FCD, measured by gross weight in FCD above the median, have significantly reduced exposure to the international equity market factor. This result is even stronger for downside risk measures, such as the market beta from the Whaley (2002) and Bawa and Lindenberg (1977) models. Coefficients of -0.0689 and -0.1003 imply a risk-reduction of 7% to 10% during periods of FCD employment, both statistically significant and economically substantial.

If funds invest in foreign currencies a depreciation of the foreign currency leads to portfolio losses when measured in the home currency of USD. I show that a strong USD adversely affects both funds engaging in FCD as well as funds not engaged in FCD measured by the negative impact of the Fed's broad nominal dollar index on fund returns.[4] This effect is less pronounced for FCD users compared to nonusers as the long-short FCD user portfolio has a significantly positive exposure to the Fed's broad nominal dollar index. This finding further supports the notion that IEF employ FCD to hedge their currency exposure.

This paper thus makes several important contributions to the existing literature. I am the first to analyze IEF use of FCD. Using detailed holdings data to identify international equity funds' FCD positions, I offer a detailed view on different types of FCD and distinguish different underlying currencies. Moreover, the higher granularity of FCD observations in holdings data enables an analysis of the time-varying nature of funds' FCD engagement. Second, I broaden the literature on fund's derivative use, which so far has mainly focused on domestic equity funds engagement in derivatives. My findings are robust to various alternative specifications and tests, such as controlling for potential nonsynchronous trading in international markets by employing Dimson's (1979) approach to measuring performance. Furthermore, following Natter et al. (2016), I introduce a dummy indicating nonuse of funds classified as overall users in the performance and risk regressions to mitigate concerns that results may be spurious because FCD user funds' performance and risk may also be different from nonuser funds in the periods, they do not employ FCD.

The structure of the remaining paper is as follows. Section 2 describes the unique data set and introduces the methodology. Section 3 presents and discusses the empirical results as well as alternative explanations. Section 4 concludes.

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[4] The Fed's broad nominal dollar index is available at http://www.federalreserve.gov/releases/h10/summary/default.htm.

2. Data and methodology

2.1 Sample construction

I obtain mutual fund data from two different sources. Data on fund returns and characteristics, such as size, turnover, fee structure, and age is taken from the CRSP Survivor-Bias-Free Mutual Fund Database (CRSP) while detailed fund level holding information is gathered from Morningstar. As CRSP reports data at share class level, I aggregate all variables to fund level by value-weighting each share class by its respective total net assets (TNA), except for TNA, age, and load information. TNA is the sum of all individual share class TNA, fund age is the logarithm of the oldest share class age, and load information is based on the largest share class.

To focus on the international activity of mutual funds, I concentrate on actively managed international equity funds. IEF have their main investment scope in non-US markets and therefore invest mostly in foreign currencies. Thus, they are more likely to employ FCD than global equity funds which may also have a significant fraction of their assets invested in domestic US assets. To ensure comparability among mutual funds, I only consider funds with a broad international focus, i.e. single country or region funds are not considered.[5] Further, I eliminate all index funds flagged by CRSP or identified based on their name as in Amihud and Goyenko (2013). Funds with less than 15 million assets under management, less than 12 monthly observations, and without lagged quarterly information are discarded. In 1997 the "short-short" rule, which made short-term trading unattractive, was repealed, increasing the willingness of funds to use derivatives (Bae and Yi, 2008). Therefore, 1997 constitutes a

[5] All funds with Lipper style code equal to International Equity Income (IEI), International Funds(IF), International Large-Cap Core (ILCC), International Large-Cap Growth (ILCG), International Large-Cap Value (ILCV), International Multi-Cap Core (IMLC), International Multi-Cap Growth (IMLG), International Multi-Cap Value (IMLV), International Small-Cap (IS), International Small/Mid-Cap Core (ISMC), International Small/Mid-Cap Growth (ISMG), or International Small/Mid-Cap Value (ISMV) are selected.

structural break. Furthermore, to assess the dynamic effect of FCD on performance and risk, daily fund return data is necessary to compute time-varying performance and risk measures. This data is only available from the end of 1998. Thus, the sample begins in January 1999 and runs through December 2014.

Morningstar, in contrast to the Thomson holdings database, widely used in holdings based equity fund studies, includes derivatives holdings for all funds and thus facilitates the analysis of FCD. Similar to Cici and Palacios (2015), I use string-screening algorithms based on fund holding names to identify a fund's FCD holdings. Holdings containing the expression "Forward" in companion with "Currency", "Foreign Exchange", "Exchange Contract", or "FX" are flagged as foreign currency forwards. In similar fashion, foreign currency swaps, foreign currency futures, and foreign currency options are classified. I identify FCD currency by screening for the respective currency name or its official abbreviation.[6] To control for falsely identified FCD, I visually inspect the identified holdings. This procedure yields 494 funds with a total of 56,100 monthly (17,390 quarterly) observations.

2.2 Performance measurement

To analyze the performance of international equity funds, I use the following model:

$$ER_{i,d} = \alpha_{i,t} + \beta_{i,t}^{mkt}\, ER_{mkt,d} + \beta_{i,t}^{smb}\, SMB_d + \beta_{i,t}^{hml}\, HML_d + \varepsilon_{i,d}. \qquad (1)$$

Here, $ER_{i,d}$ is fund *i*'s return in excess of the risk-free rate for day *d* of quarter *t*.[7] $ER_{mkt,d}$ is the international market return, SMB_d the international size factor, and HML_d the international value factor on day *d*. Equation (1) nests the CAPM and Fama and French's (1993) 3-factor model. Unfortunately, daily values for the factors of Equation (1) are not freely available. Furthermore, Cremers et al. (2013) argue that performance models based on factors are misspecified as they do

[6] For example, the European currency is identified via "EUR" or "EURO".

[7] Data on the risk-free rate is from Kenneth French's homepage.

not constitute investable benchmarks. Therefore, I follow Breloer et al. (2014) and Hiraki et al. (2015) and use investable indices to define the factors. $ER_{mkt,d}$ is given by the daily return of the MSCI All Country World ex USA Investable Market Index (MSCI ACWI EX USA IMI).[8,9,10] The size factor SMB_d is given by the the average return of the MSCI ACWI EX USA Small Value and the MSCI ACWI EX USA Small Growth Index minus the average return of the MSCI ACWI EX USA Large Value and the MSCI ACWI EX USA Large Growth Index. The value factor HML_d is calculated as the average return of the MSCI ACWI EX USA Small Value and the MSCI ACWI EX USA Large Value Index minus the average return of the MSCI ACWI EX USA Small Growth and the MSCI ACWI EX USA Large Growth Index.

If funds correctly use FCD to hedge their exposure to international equity markets during adverse currency movements and earn risk premia during beneficial currency movements, standard measures of symmetric risk and performance may not be appropriate. Thus, I employ Bawa and Lindenberg's (1977) as well as Whaley's (2002) approach to measure downside risk. Bawa and Lindenberg (1977) focus on the semi-variance instead of the symmetric variance:

$$\alpha_{BL,i,t} = R_{i,d} - \beta_{BL,i,t}^{mkt}\left[R_{mkt,d}\right] \tag{2}$$

$$\text{where } \beta_{BL,i,t}^{mkt} = \frac{cov\left(R_{i,d}, R_{mkt,d} | R_{mkt,d} < 0\right)}{var\left(R_{mkt,d} | R_{mkt,d} < 0\right)}$$

Here, $\alpha_{BL,i,t}$ is fund *i*'s Bawa and Lindenberg (1977) alpha in quarter *t*, $R_{i,d}$ is the return of fund *i* on day *d*, and $R_{mkt,d}$ is the market return on day *d* measured by the MSCI ACWI EX USA IMI. Whaley's (2002) downside risk measure is specified similarly to Equation (2):

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[8] For details on the index, see https://www.msci.com/documents/10199/3588d896-0a28-4762-b355-3844c8c81ff8.

[9] Index data is obtained from Datastream.

[10] To control for potential home market bias, in robustness analyses all factors are based on the MSCI All Country World Investable Market Index including the US.

$$\alpha_{Whaley,i,t} = R_{i,d} - \beta_{Whaley,i,t}^{mkt}\left[R_{mkt,d}\right] \quad (3)$$

where $\beta_{Whaley,i,t}^{mkt} = \frac{cov\left(R_{i,d},R_{mkt,d} | R_{i,d}<0,R_{mkt,d}<0\right)}{var\left(R_{mkt,d} | R_{i,d}<0,R_{mkt,d}<0\right)}$

Following Natter et al. (2016), fund returns as well as market returns on the factors given in Equation (1) are orthogonalized to control for size and book-to-market effects in the models of Bawa and Lindenberg (1977) and Whaley (2002).

3. Empirical analysis of foreign currency derivatives (FCD) use

3.1 Descriptive statistics on the fund sample and foreign currency holdings

Table 1 shows descriptive statistics for the sample of international equity funds. The average IEF has USD 1.109 bn. in assets under management and belongs to a family with USD 130.884 bn. TNA. The average fund is 8.44 years old. 74.44% of the sample funds charge front or back loads. The average turnover and expense ratios as well as the percentage of assets held in cash are comparable to domestic equity funds (e.g., Pastor et al., 2015). Positive net flows of 1.61% underline the growth of the IEF market over the sample period. IEF return 0.47% per month. As shown in previous studies (e.g., Busse et al., 2014; Breloer et al., 2014), international funds are not able to earn abnormal returns as their CAPM as well as Fama and French (1993) alphas are -0.15% and -0.19% per month. Regarding fund risk, volatility is 5.2% per month. CAPM as well as Fama and French (1993) market betas are below but close to one. The downside risk measures of Bawa and Lindenberg (1977) and Whaley (2002) are 1.7685 and 1.1827, respectively, implying strong exposure to downside risk of international equity funds.

[Insert Table 1 here.]

To get a first impression of IEF's investment scope, Table 2 shows the distribution of the percentage of fund holdings held in the respective currency. On average, IEF hold 10.72% of their assets in their domestic currency (USD). The most popular currency is the Euro (EUR) with nearly 20% of average fund holdings, followed by the Japanese Yen (JPY) with 13.62%

and the British Pound (GBP) with 12.72% of average fund holdings. The Swiss Franc (CHF) makes up 5.22% of average fund holdings, while Canadian (CAD), Australian (AUD) and Hong Kong (HKD) Dollar on average constitute 2.27%, 2.61%, and 3.04% of IEF portfolios, respectively. All other currencies individually make up less than 1.57% of portfolio holdings indicating a diversified international asset allocation and reflecting the international investment scope of the sample funds. These results are in line with the country weights of IEF shown by Hiraki et al. (2015).

[Insert Table 2 here.]

3.2 Descriptive statistics on FCD engagement

Table 3 shows that 55.26% of IEF use at least one FCD over the course of the sample period. The most important FCD are foreign currency forwards (52.83% user funds) and futures (20.24% user funds). Foreign currency swaps (0.61%) and foreign currency options (3.85%) are of less relevance. Most investments take place in FCD on the major currencies, especially the EUR as nearly half of all funds (42.91%) use FCD on EUR over the sample period. GBP (37.04%) and JPY (37.04%) follow. Thus, the most important holding currencies are also the most popular currencies underlying FCD. Although CHF is the fourth most important holding currency, it is used as the underlying for FCD by only 15.99% of all funds. CAD, AUD, HKD as well as the Scandinavian currencies Swedish Krona (SEK), Danish Krone (DKK), and Norwegian Krone (NOK) are all more popular than CHF in terms of FCD use, although they make up a smaller fraction of funds holdings. FCD on other currencies are also used extensively, even for those currencies that make up small fractions of fund holdings (e.g. Singapore Dollar (SGD) with 23.48% user funds).

[Insert Table 3 here.]

User funds, however, are not constantly engaged in FCD over the sample period. Rather, they employ FCD tactically as shown by the “Using” column of Table 3. While FCD are used by more than half of all funds, they are only used in 18.04% of all fund-quarters. This means, that the average user fund employs FCD in only a third of all months, implying time-varying decision-making regarding FCD employment. Results for individual FCD types and currencies are consistent with this finding. If funds employ FCD they make up a substantial gross weight of 5.48% of all holdings, with FCD on EUR being the largest individual FCD type with nearly 2% of average holdings.

[Insert Table 4 here.]

Table 4 shows the main variables for IEFthat use FCD at least once and those funds that do not use any FCD during the sample period. Regarding the average fund characteristics only family size, age, and net flow differ. User funds belong to smaller fund families and are significantly older. They experience only half the positive investor inflow compared to nonuser funds. Concerning performance characteristics, there are no clear patterns when means are compared. When comparing median performance measures, user funds seem to underperform nonuser funds, with all measures being negative and the net return and CAPM alpha difference of 0.1% and 0.07% per month significant at the 1% level. Systematic exposure to international equity markets, especially downside exposure, is lower for users than for nonusers, albeit mostly insignificantly so.

3.3 Mutual fund FCD engagement, performance, and risk

The related literature on domestic mutual funds' use of derivatives has mainly focused on options. Lynch-Koski and Pontiff (1999) as well as Cici and Palacios (2015) find no difference in performance and risk characteristics for users and nonusers of equity options. Natter et al. (2016) provide evidence in favor of option use leading to higher risk-adjusted returns and lower market risk. Cao et al. (2011) find no significant differences in return distributions for international funds using any kind of derivative in comparison to nonusers. Further, they also do not find any impact of FCD use on fund performance for all fund types.

Their study, however, only focuses on raw return distributions for a limited sample period during the Asian crisis and thus does not lend itself for general conclusions. Chen (2011) analyzes hedge funds and finds that use of FCD is most prevalent in global macro hedge funds. Additionally, he finds lower total, market, and idiosyncratic risk for hedge funds using FCD. However, Chen (2011) does not consider the time element of FCD use, as his results are based on cross-sectional analysis only. Furthermore, regulation differs severely between hedge funds and mutual funds leading to potential differences in FCD use.

Hence, the relation between FCD use and fund performance and risk characteristics is not clear a priori. If fund managers are able to time currency movements or pick currencies, their funds should have higher risk-adjusted performance in comparison to funds not employing FCD. Speculating on currency movements via FCD should lead to higher exposure towards international equity markets. Therefore, engaging in FCD allows IEF to speculate on currency movements as a potential additional alpha source. If, on the other hand, IEF employ FCD to hedge their foreign currency exposure they should have lower international equity market exposure, with potentially lower performance. Thus, the sign and significance of FCD's relation to fund performance and risk is a question open to empirical findings.

To analyze this relation, I construct a portfolio long in funds engaging in FCD and short in funds not engaging in FCD. Table 5 shows monthly performance and risk measures for the equal-weighted portfolio (Panel A) and value-weighted portfolio (Panel B). For the equal-weighted portfolio performance is negative with monthly (risk-adjusted) returns ranging from -0.0007 (net returns) to -0.0005 for the international Fama and French (1993) 3-factor model. This indicates yearly underperformance of 60 to 84 basis points. The use of global instead of international benchmark factor returns does not affect the results. T-values correcting for autocorrelation and heteroscedasticity using Newey and West's (1987) approach are below -1.99 and thus show statistical significance for all coefficients at the 5%

level. Coefficients on risk are also significantly different from zero with t-values ranging from -4.89 for the international CAPM market beta to -5.93 for the international Fama and French (1993) market beta. This implies that the long-short portfolio has a negative exposure to the international equity market factor and nonusers thus have higher exposure than FCD user funds.

[Insert Table 5 here.]

For the value-weighted portfolio, performance is not statistically distinguishable from zero. The risk results of the equal-weighted portfolio, however, also apply to the value-weighted portfolio. Coefficients for the market betas are even more negative and significantly different from zero. Hence, the results are a first indication that IEF employ FCD to hedge their currency exposure.

As portfolio results are, at least partly, influenced by the weighing scheme, it is natural to assume that factors other than FCD employment, such as size, may influence fund performance and risk. Furthermore, the impact of FCD employment may vary according to the amount of FCD used. Therefore, to control for fund characteristics associated with performance and the varying degree of FCD usage, I employ the following panel regressions of fund performance on the FCD dummy and fund controls as well as time and investment style fixed effects:

$$Performance_{i,t} = \varphi_0 + \varphi_1 Use_{i,t\text{-}1} + \sum_{j=2}^{J} \varphi_j \, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \tag{4}$$

$Performance_{i,t}$ is the risk-adjusted annualized performance in quarter t of fund i calculated via the international Fama-French (1993) 3-factor model of Equation (1) in Section 2.2 using daily net returns. In the first specification, $Use_{i,t\text{-}1}$ is the dummy variable $FCD_{i,t\text{-}1}$ indicating

FCD employment of fund i during quarter t-1.[11] In the second specification, $Use_{i,t\text{-}1}$ is split up into the dummies $Light_{i,t\text{-}1}$ and $Heavy_{i,t\text{-}1}$ indicating funds with FCD investments below (above) the median, measured by gross holdings weight. As $Controls_{i,j,t\text{-}1}$ the fund characteristics of Table 1 are used. Following Petersen (2009), standard errors are clustered by both fund and quarter.

[Insert Table 6 here.]

The results in Panel A of Table 6 show that IEF performance, measured with the international Fama and French (1993) model, is not significantly affected by FCD engagement. The coefficient of the overall FCD dummy is -0.0003 with a t-value of -1.2 and thus not substantially different from zero. When differentiating between light and heavy engagement in FCD, column (2) shows that light engagement has an effect of -0.0005 on fund alpha with a t-value of -1.74 implying significance at the 10% level only. The coefficient on heavy engagement on the other hand is not statistically different from zero, indicating no performance impact of FCD usage. Concerning the control variables, turnover is negatively related to fund performance possibly due to trading costs in line with Carhart (1997), while net flow is positively related to performance due to performance chasing behavior of fund investors (e.g., Sirri and Tufano, 1998). Older funds have lower performance, consistent with Pastor et al. (2015). Fund size, expense ratios cash and family size are not significantly related to international fund performance.

To assess the effect of FCD engagement on funds' international market exposure, I use the following panel regressions including time and investment style fixed effects:

$$Risk_{i,t} = \varphi_0 + \varphi_1 Use_{i,t\text{-}1} + \sum_{j=2}^{J} \varphi_j \, Controls_{i,j,t\text{-}1} + \eta_{i,t}. \quad (5)$$

[11] In unreported analyses, using contemporaneous right hand side variables does not affect the results.

$Risk_{i,t}$ is the market beta from the international Fama and French (1993) regression of Equation (1) calculated for each quarter t using daily net returns. $Use_{i,t\text{-}1}$ and $Controls_{i,j,t\text{-}1}$ are defined as in Equation (4). Panel B displays the results. Column (3) shows that overall FCD engagement has no significant impact on IEF risk, with a coefficient of -0.0092 and a t-value of -1.45. The control variables show that funds with higher turnover and lower expense ratios have higher market betas. Fund age is positively related to market risk. When discriminating between light and heavy FCD engagement, Column (4) shows that heavy FCD engagement is significantly related to funds' international equity market exposure. While funds that are only lightly invested in FCD do not differ from nonusers with respect to their market beta (coefficient of 0.0007 and t-value of 0.10), heavy users decrease their market risk by nearly 2% (coefficient of -0.0193 and t-value of -2.38). Thus, IEF decrease their exposure to the foreign equity market factor and thus their exposure to foreign currency movements by heavily engaging in FCD.

To give further support to this finding, Table 7 shows results for other performance models. Regardless of the performance model employed, FCD engagement does not affect fund performance in Panel A, with all coefficients statistically indistinguishable from zero. Turning to Panel B, risk remains severely affected. Overall fund volatility is significantly lower for funds heavily engaged in FCD with a coefficient of -0.0003 and a t-value of -2.21. The results for the international CAPM do not differ from the main results of Table 6 using Fama and French's (1993) 3-factor model. The coefficient of -0.0181 (t-value -1.97) again indicates a decrease in foreign equity market exposure of nearly 2% for heavy FCD users.

Funds may use derivatives, such as FCD, to create asymmetric return profiles. They try to keep their exposure to positive exchange rate movements while decreasing the impact of adverse movements. Consequentially, IEFs' exposure to negative international equity market movements measured in USD could be managed via FCD. When explaining the downside risk measure of Bawa and Lindenberg (1977), the coefficient of heavy FCD engagement therefore is larger than for the standard risk measures. A coefficient of -0.1003 (t-value of -3.15) indicates that IEF are able to decrease their exposure to downside risk concerning international equity markets by an economically substantial 10% when heavily engaged in FCD. A similar result is given by Whaley's (2002) downside risk measure. The coefficient of -0.689 (t-value -3.38) implies a downside risk reduction of heavy FCD users by nearly 7%.

Compared to funds not engaged in FCD, even light FCD engagement decreases a fund's exposure to downside risk of the international equity index. Coefficients of -0.0717 (t-value of -2.49) for Bawa and Lindenberg's (1977) model and -0.0415 (-2.19) for Whaley's model are both statistically negative and imply a risk reduction of 7% and 4%, respectively. This is less than the risk reduction attained via heavy FCD engagement, but still of substantial economic magnitude. Thus, IEF risk is severely decreased by their engagement in FCD indicating that funds use FCD to hedge their foreign exchange risk.

[Insert Table 7 here.]

To further support the notion that funds employ FCD to hedge against adverse changes in foreign currency values, Table 8 shows how foreign currency holdings are related to FCD engagement. If a fund uses FCD to hedge foreign exchange risk, the underlying currency of the FCD should be the same as the existing portfolio positions the fund wants to hedge. The results of Table 2 and Table 3 imply that FCD and portfolio currencies are somewhat similar. To strengthen this finding, I run a probit regression explaining FCD engagement with non-FCD portfolio holdings (non-FCD portfolio holdings changes) in foreign currencies, denominated by the coefficient FX holdings (changes). Fund characteristics of Table 1 are incorporated as control variables. For ease of interpretation, all explanatory variables are standardized as in Clifford et al. (2014).

[Insert Table 8 here.]

Table 8 displays the results. FX holdings has a positive coefficient of 0.1753 (z-value of 16.91). This implies that a one standard deviation increase in non-FCD foreign currency holdings increases a fund's likelihood to use FCD by nearly 17%. The control variables are mainly insignificant. Only family size is significantly related to FCD engagement, with a coefficient of -0.0422 suggesting that funds belonging to larger families are less likely to engage in FCD. Results for FX holdings changes presented in Column (2) also show a positive relation to FCD engagement probability. Consequentially, a fund's decision to engage in FCD is positively influenced by the amount it holds in foreign currencies.

Column (3) and (4) display the results of a panel regression of (changes in) FCD holdings weight on FX holdings (changes) as well as time and style fixed effects. The coefficient on FX holdings (change) is 0.0877 (0.0464) with a t-value of 2.93 (2.84) implying that when funds increase their non-FCD foreign currency holdings, FCD holdings also rise. This, in combination with the finding of decreased international market exposure for FCD users, further supports the notion that IEF do not use FCD to diversify their existing foreign currency exposure by speculating on currency movements. Rather, they use FCD to hedge the foreign exchange risk associated with their existing portfolio.

If funds use FCD to hedge their foreign exchange risk, changes in USD strength compared to foreign currencies should affect FCD users less than nonuser funds. To test this, I run the following regression:

$$Portfolio_t = \gamma_0 + \gamma_1 FED_t + \upsilon_t, \qquad (6)$$

Where $Portfolio_t$ is either the equally weighted portfolio return of funds not engaged in FCD during the respective month (nonusers), of funds engaged in FCD in the respective month (users), or a portfolio long in FCD users and short in nonusers (long-short portfolio) in month *t*. FED_t is USD strength measured by the value or changes in the value of the Federal Reserve's Broad Nominal Dollar Index (Panel A) and Major Nominal Dollar Index (Panel B).[12,13]

[Insert Table 9 here.]

Table 9 shows the results. The coefficient on the Broad Nominal Dollar Index value is significant and negative for nonusers (-1.2211 and t-value of -4.55) as well as for FCD users (-1.1713, t-value -4.48). This indicates that IEF are adversely affected by a stronger USD as their investments denominated in foreign currencies are less valuable when measured in USD. However, the positive coefficient of 0.0499 (t-value 2.99) of the long-short portfolio shows that there is a significant difference in the response of fund returns to USD strength for FCD users and nonusers. The adverse effect of a stronger USD is 5% less severe for IEF engaged in FCD than for funds not using FCD.

Regarding changes in the Broad Nominal Dollar Index, this finding holds. The results are also supported by the coefficients on the (changes in the) Major Nominal Dollar Index in Panel B. The long-short portfolio implies a reduction in the adverse effect of USD strength on fund returns by 8.85% (t-value of 2.98) for the index value and 5.72% (t-value of 2.00) for index changes. Consequentially, funds use FCD to hedge their foreign exchange risk.

3.4 Alternative explanations and robustness checks

To mitigate concerns that the results presented so far are due to alternative explanations, several robustness checks are carried out. As daily IEF returns may be affected by non-

[12] The indices are available at http://www.federalreserve.gov/releases/h10/summary/default.htm

[13] The broad nominal dollar index is the weighted mean of the USD exchange rate to 26 foreign currencies. The major nominal dollar index is the weighted mean of the USD exchange rate to the 7 major foreign currencies. For details on index construction please refer to Federal Reserve Bulletin (2005): Indexes of the Foreign Exchange Value of the Dollar available at http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf

synchronous trading (Chalmers et al., 2001), performance regressions based on daily fund returns may be misleading. To control for this staleness in fund returns, Dimson (1979) suggests using lagged and leaded daily factor returns. Panel A of Table 10 displays results for Equation (4) and (5) where $Performance_{i,t}$ and $Risk_{i,t}$ are calculated using the international version of Fama and French's (1993) 3-factor model of Equation (1) augmented with the international market, size, and value factor returns of days *d* - 1 and *d* + 1. The results confirm that heavy FCD engagement decreases international market risk, while performance remains unaffected.

[Insert Table 10 here.]

Net returns employed so far are relevant when assessing how fund shareholders may benefit from their investment in IEF. To evaluate the performance generated by fund managers before fees, Panel B shows results using daily gross returns to calculate quarterly fund performance. The results are unchanged from using net returns, further supporting my main findings.

Funds using FCD may have less exposure to the international equity market factor, regardless of their investment in FCD. However, Table 8 already shows that a fund's market beta is not a significant predictor of FCD engagement, mitigating concerns that the main findings are driven by endogeneity. Furthermore, only heavy engagement is associated with less international market factor exposure. Nevertheless, Panel C of Table 10 also shows results for Equation (4) and (5) augmented with a *Nonusing* dummy. This dummy equals one during quarters when a fund that has employed FCD in previous periods is not engaged in FCD during the respective quarter. The coefficient on the *Nonusing* dummy is statistically indistinguishable from zero, whereas the coefficient of heavy FCD engagement is -0.0196 with a t-value of -2.23 in line with the previous findings.

Finally, I also measure performance with global factor benchmarks including the US market instead of international factor benchmarks without the US in order to mitigate concerns, that a decrease in foreign market risk is offset by an increase in domestic market risk. Results presented in Panel D are not affected by this change of methodology. Hence, the main finding that international mutual funds engage in FCD to hedge their international market and thus currency exposure holds.

4. Summary and conclusion

This paper is the first to examine in detail the use of foreign currency derivatives (FCD) of international equity mutual funds (IEF). This is important because many IEF use such instruments and the effect on performance and risk are not clear a priori. My findings show that, the majority of funds use currency forwards, while only few funds engage in currency swaps, futures, or options. The amount invested into FCD is economically substantial and focuses on currencies already prevalent in a fund's portfolio. The empirical results suggest that funds engaged in FCD do not differ with regard to their performance. Their exposure to the international equity market factor, however, is significantly lower during times of heavy FCD engagement. Since FCD can only affect the impact of foreign currency value changes on funds, IEF thus employ FCD to hedge their foreign currency risk. These findings give guidance to investors investing in international markets through international equity funds and to regulators concerned with mutual fund derivatives use.

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Tables

Table 1
Overall summary statistics

	Mean	Median	Std. Dev.
Fund Characteristics			
TNA ($mil)	1,109	251	4,071
Family TNA ($mil)	130,884	27,204	307,471
Age (Years)	8.4369	7.0000	6.2050
Turnover ratio (% TNA, p.a)	0.7494	0.6528	0.4995
Load dummy	0.9216	1.0000	0.2303
Expense ratio (% TNA, p.a)	0.0133	0.0130	0.0041
Cash (% TNA)	0.0387	0.0317	0.0604
Net flow (% TNA)	0.0161	0.0089	0.0312
Performance			
Excess net return	0.0047	0.0051	0.0046
CAPM alpha	-0.0015	-0.0015	0.0028
Fama-French alpha	-0.0003	-0.0005	0.0026
Bawa Lindenberg alpha	0.0028	0.0029	0.0057
Whaley alpha	-0.0097	-0.0092	0.0048
Risk			
Volatility	0.0520	0.0527	0.0108
CAPM beta	0.9653	0.9698	0.1071
Fama-French beta	0.9590	0.9686	0.0956
Bawa Lindenberg beta	1.7685	1.5809	1.8882
Whaley beta	1.1827	1.0520	0.9595

This table presents mean, median, and standard deviation of fund characteristics for 494 actively managed international equity funds with entries in Morningstar and the CRSP mutual fund database during the period 1999-2014.

Table 2
Foreign currency holdings

	Mean	Std. Dev.	25%	Median	75%
US Dollar (USD)	0.1072	0.1219	0.0463	0.0731	0.1138
Euro (EUR)	0.1917	0.0803	0.1589	0.1973	0.2396
Japanese Yen (JPY)	0.1362	0.0580	0.1055	0.1436	0.1745
Swiss Franc (CHF)	0.0522	0.0291	0.0324	0.0520	0.0685
British Pound (GBP)	0.1272	0.0510	0.1016	0.1331	0.1589
Canadian Dollar (CAD)	0.0227	0.0277	0.0045	0.0150	0.0308
Australian Dollar (AUD)	0.0261	0.0210	0.0118	0.0217	0.0362
Hong Kong Dollar (HKD)	0.0304	0.0232	0.0155	0.0255	0.0374
Swedish Krona (SEK)	0.0156	0.0104	0.0088	0.0148	0.0203
Danish Krone (DKK)	0.0075	0.0077	0.0021	0.0054	0.0099
Norwegian Krone (NOK)	0.0096	0.0105	0.0033	0.0074	0.0129
Brazilian Real (BRL)	0.0076	0.0106	0.0002	0.0038	0.0107
Korean Won (KRW)	0.0119	0.0126	0.0024	0.0091	0.0171
Mexican Peso (MXN)	0.0042	0.0059	0.0000	0.0021	0.0061
Malysian Ringgit (MYR)	0.0015	0.0046	0.0000	0.0000	0.0009
New Zealand Dollar (NZD)	0.0014	0.0039	0.0000	0.0001	0.0011
Polish Zloty (PLN)	0.0007	0.0028	0.0000	0.0000	0.0002
Singapore Dollar (SGD)	0.0111	0.0111	0.0044	0.0088	0.0148
Thai Baht (THB)	0.0020	0.0039	0.0000	0.0004	0.0021
Taiwan Dollar (TWD)	0.0058	0.0095	0.0001	0.0029	0.0074
South African Rand (ZAR)	0.0038	0.0071	0.0000	0.0011	0.0040
Turkish Lira (TRY)	0.0014	0.0042	0.0000	0.0000	0.0009
Hungarina Forint (HUF)	0.0005	0.0016	0.0000	0.0000	0.0001
Indonesian Rupiah (IDR)	0.0015	0.0035	0.0000	0.0001	0.0015
Russian Ruble (RUB)	0.0012	0.0088	0.0000	0.0000	0.0007
Chinese Renminbi (CNY)	0.0015	0.0023	0.0000	0.0005	0.0021

This table presents summary statistics of fund holdings in foreign currency as percentage of fund TNA for 494 actively managed international equity funds with entries in Morningstar and the CRSP mutual fund database during the period 1999-2014.

Table 3
Foreign currency derivatives use

	Users	Using	gross market value ($mil)	net market value ($mil)	gross weight (% TNA)	net weight (% TNA)
FCD	0.5526	0.1804	63.57	-1.62	0.0548	0.0022
FX Swaps	0.0061	0.0002	39.11	-33.86	0.0583	-0.0510
FX Futures	0.2024	0.0235	24.86	2.98	0.0246	-0.0018
FX Forwards	0.5283	0.1656	65.21	-2.46	0.0561	0.0025
FX Options	0.0385	0.0042	20.61	12.04	0.0063	0.0045
FCD EUR	0.4291	0.0924	19.89	0.44	0.0196	0.0006
FCD JPY	0.3704	0.0755	21.86	-1.90	0.0175	-0.0012
FCD CHF	0.1599	0.0278	23.34	-2.33	0.0165	-0.0005
FCD GBP	0.3704	0.0655	17.84	-0.93	0.0164	0.0000
FCD CAD	0.2490	0.0398	18.35	-3.24	0.0116	-0.0011
FCD AUD	0.3016	0.0530	11.06	0.16	0.0084	0.0008
FCD HKD	0.3016	0.0512	14.70	0.44	0.0059	0.0006
FCD SEK	0.2652	0.0462	11.32	1.13	0.0057	0.0011
FCD DKK	0.2328	0.0325	2.34	-0.25	0.0014	0.0002
FCD NOK	0.1964	0.0357	6.94	-1.79	0.0039	-0.0006
FCD BRL	0.1255	0.0119	0.69	-0.05	0.0010	0.0000
FCD KRW	0.1559	0.0161	3.51	-0.52	0.0044	0.0000
FCD MXN	0.1194	0.0145	2.33	-1.98	0.0022	-0.0007
FCD MYR	0.0607	0.0053	1.49	0.07	0.0047	0.0001
FCD NZD	0.0749	0.0118	5.87	-0.19	0.0014	0.0000
FCD PLN	0.0526	0.0060	8.45	-6.89	0.0027	-0.0004
FCD SGD	0.2348	0.0424	20.46	-0.86	0.0068	-0.0001
FCD THB	0.0769	0.0052	0.43	-0.38	0.0001	0.0000
FCD TWD	0.1235	0.0188	1.36	1.19	0.0019	0.0014
FCD ZAR	0.0972	0.0112	0.60	-0.15	0.0006	0.0001
FCD TRY	0.0607	0.0053	1.51	-1.32	0.0004	-0.0001
FCD HUF	0.0425	0.0070	5.77	-5.61	0.0005	-0.0002
FCD IDR	0.0850	0.0069	2.71	2.53	0.0009	0.0006
FCD RUB	0.0061	0.0003	0.10	-0.03	0.0003	0.0000
FCD CNY	0.0243	0.0011	0.65	-0.38	0.0009	-0.0007
FCD other currencies	0.4818	0.1061	19.32	1.62	0.0303	0.0024

This table presents descriptive statistics on the usage of foreign currency derivatives (FCD) by international mutual funds. The sample consists of 494 actively managed international equity funds with entries in Morningstar and the CRSP mutual fund database during the period 1999-2014. FCD comprises fund engagement in FX Swaps, Futures, Forwards, and/or options. Used indicates the percentage of funds that use the respective FCD at least once during the sample period. Engaged indicates the percentage of fund quarters in which the respective FCD is employed. Gross (net) market value is the gross (net) economic exposure of the respective FCD in USD of the relevant position. Gross (net) weight is the gross (net) market value of the respective FCD as a fraction of a fund's TNA.

Table 4

Summary statistics for foreign currency derivatives (FCD) users and nonusers

	Mean				Median			
	User	Nonuser	Difference		User	Nonuser	Difference	
Fund Characteristics								
TNA ($mil)	1,206	989	216		295	200	95	***
Family TNA ($mil)	62,210	215,716	-153,506	***	16,710	55,304	-38,594	***
Age (Years)	9.6264	6.9675	2.6590	***	8.7083	4.7917	3.9167	***
Turnover ratio (% TNA, p.a)	0.7728	0.7205	0.0524		0.6784	0.5800	0.0984	
Load dummy	0.9099	0.9361	-0.0262		1.0000	1.0000	0.0000	
Expense ratio (% TNA, p.a)	0.0135	0.0131	0.0003		0.0132	0.0125	0.0007	
Cash (% TNA)	0.0385	0.0389	-0.0004		0.0328	0.0299	0.0029	***
Net flow (% TNA)	0.0108	0.0226	-0.0117	***	0.0066	0.0146	-0.0079	***
Performance								
Excess net return	0.0034	0.0033	0.0001		0.0033	0.0042	-0.0010	***
CAPM alpha	-0.0007	-0.0003	-0.0004		-0.0010	-0.0002	-0.0007	***
Fama-French alpha	-0.0004	-0.0002	-0.0002		-0.0008	-0.0002	-0.0006	
Bawa Lindenberg alpha	0.0029	0.0026	0.0003		0.0027	0.0032	-0.0005	
Whaley alpha	-0.0095	-0.0100	0.0005		-0.0093	-0.0088	-0.0004	
Risk								
Volatility	0.0522	0.0519	0.0003		0.0525	0.0531	-0.0006	
CAPM beta	0.9626	0.9686	-0.0060		0.9681	0.9755	-0.0075	
Fama-French beta	0.9517	0.9681	-0.0164		0.9662	0.9701	-0.0039	***
Bawa Lindenberg beta	1.6546	1.9224	-0.2678		1.4754	1.8229	-0.3475	
Whaley beta	1.1111	1.2711	-0.1599		1.0147	1.1109	-0.0962	

This table reports descriptive statistics for 273 foreign currency derivative (FCD) user and 221 nonuser funds. The sample consists of actively managed international equity funds with entries in Morningstar and the CRSP mutual fund database during the period 1999-2014. User funds use at least one FCD at least once during the sample period and nonusers completely avoid using FCD. Differences in means are tested using two-sided, unpaired mean comparison tests. Differences in medians are tested using Wilcoxon rank-sum tests. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5

Portfolios sorted by foreign currency derivatives engagement

	Net returns	Gross returns	CAPM	Fama-French	CAPM global	Fama-French global
Panel A: Equally weighted portfolio						
(risk-adjusted) return	-0.0007***	-0.0007***	-0.0006**	-0.0005**	-0.0006**	-0.0005**
	(-2.69)	(-2.69)	(-2.34)	(-1.99)	(-2.28)	(-2.03)
Market beta			-0.0241***	-0.0267***	-0.0284***	-0.0310***
			(-4.45)	(-5.05)	(-5.25)	(-4.28)
Panel B: Value weighted portfolio						
(risk-adjusted) return	-0.0005	-0.0005	-0.0003	-0.0001	-0.0003	-0.0001
	(-0.77)	(-0.77)	(-0.49)	(-0.25)	(-0.48)	(-0.17)
Market beta			-0.0392***	-0.0450***	-0.0416***	-0.0507***
			(-2.90)	(-3.44)	(-2.78)	(-3.35)

This table shows monthly performance of portfolios sorted on foreign currency derivatives (FCD) engagement. The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. At the end of each month *t*, funds are sorted into the long (short) portfolio based on their engagement (nonuse) of FCD. In panel A, funds are weighted equally in each portfolio, while in panel B, funds are weighted according to their TNA. Performance is measured with monthly net and gross fund returns, the international (global) CAPM and international (global) Fama-French Model. ***, **, * denote 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.

Table 6
Performance and risk regression

	Panel A: Alpha		Panel B: Market beta	
	(1)	(2)	(3)	(4)
FCD	-0.0003		-0.0092	
	(-1.20)		(-1.45)	
Light		-0.0005*		0.0007
		(-1.74)		(0.10)
Heavy		-0.0002		-0.0193**
		(-0.58)		(-2.38)
Size	0.0001	0.0001	-0.0034	-0.0034
	(1.18)	(1.18)	(-1.35)	(-1.35)
Turnover	-0.0005*	-0.0005*	0.0327***	0.0330***
	(-1.75)	(-1.76)	(6.21)	(6.23)
Expense	-0.0278	-0.0280	-2.6949***	-2.6878***
	(-1.23)	(-1.25)	(-3.39)	(-3.38)
Net Flow	0.0006**	0.0006*	-0.0103	-0.0101
	(1.96)	(1.96)	(-1.39)	(-1.37)
Age	-0.0004***	-0.0004***	0.0136***	0.0138***
	(-3.15)	(-3.19)	(3.35)	(3.40)
Cash	0.0009	0.0009	-0.1808***	-0.1826***
	(1.05)	(1.09)	(-3.04)	(-3.07)
Family Size	0.0001	0.0000	-0.0030*	-0.0030*
	(0.89)	(0.85)	(-1.81)	(-1.76)
Intercept	-0.0183***	-0.0183***	0.9568***	0.9553***
	(-11.98)	(-12.00)	(24.70)	(24.73)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.56	0.56	0.43	0.43
N	17,390	17,390	17,390	17,390

This table shows results of a panel regression of fund performance on foreign currency derivative (FCD) use. The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. Alpha (market beta) is the intercept (slope on the international market index) from the international Fama and French (1993) 3-factor model. Performance and risk are calculated for each fund and quarter individually using daily net fund returns. FCD is a dummy variable set to one when a fund uses foreign currency derivatives in the respective quarter and zero otherwise. $Light_{i,t-1}$ ($Heavy_{i,t-1}$) is a dummy variable equal to one when a fund has FCD investments below (above) the median, measured by gross holdings weight in the respective quarter and zero otherwise. All explanatory variables are lagged one quarter. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and quarter following Petersen (2009) are given in parentheses.

Table 7
Performance and risk regression - Other risk measures

	Panel A: Performance				Panel B: Risk			
	Return	CAPM	Bawa-Lindenberg	Whaley	Volatility	CAPM	Bawa-Lindenberg	Whaley
Light	-0.0000	-0.0006*	-0.0002	0.0003	-0.0000	0.0025	-0.0717**	-0.0415**
	(-1.02)	(-1.80)	(-0.71)	(0.59)	(-0.74)	(0.36)	(-2.49)	(-2.19)
Heavy	-0.0000	-0.0001	-0.0000	0.0005	-0.0047**	-0.0181**	-0.1003***	-0.0689***
	(-1.15)	(-0.33)	(-0.14)	(0.57)	(-2.21)	(-1.97)	(-3.15)	(-3.38)
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	0.90	0.34	0.54	0.87	0.92	0.30	0.55	0.51
N	17,390	17,390	17,390	17,390	17,390	17,390	17,390	17,390

This table shows results of a panel regression of fund performance on FCD use. The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. In Panel A, performance is measured with net returns, the international CAPM, Bawa and Lindenberg's (1977) model, and Whaley's (2002) model. In Panel B, risk is measured with net return volatility, the market beta from the international CAPM, Bawa and Lindenberg's (1977) model, and Whaley's (2002) model. Performance and risk are calculated for each fund and quarter individually using daily net fund returns. $Light_{i,t-1}$ ($Heavy_{i,t-1}$) is a dummy variable equal to one when a fund has FCD investments below (above) the median, measured by gross holdings weight in the respective quarter and zero otherwise. All explanatory variables are lagged one quarter. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and quarter following Petersen (2009) are given in parentheses.

Table 8
Determinants of foreign currency derivatives engagement (FCD)

	FCD engagement		FCD weight	FCD weight changes
	(1)	(2)	(3)	(4)
FX holdings	0.1753***		0.0877***	
	(16.91)		(2.93)	
FX holdings change		0.0472***		0.0464***
		(12.97)		(2.84)
Size	-0.0009	-0.0045	-0.0153	-0.0010
	(0.08)	(0.36)	(1.27)	(0.58)
Turnover	0.0044	0.0125	0.0311**	0.0019
	(0.64)	(1.46)	(2.31)	(0.39)
Expense	-0.0073	-0.0167	-5.6257**	-0.3734
	(0.76)	(1.35)	(2.04)	(0.55)
Net flow	0.0020	0.0003	0.0252	-0.0215**
	(0.54)	(0.07)	(1.43)	(2.16)
Age	0.0112	0.0227*	0.0113	0.0005
	(1.05)	(1.81)	(0.80)	(0.13)
Family size	-0.0422***	-0.0404***	0.0047	-0.0007
	(4.79)	(3.49)	(0.86)	
Alpha	-0.0072	-0.0120**	0.8908	-0.8180*
	(1.45)	(2.19)	(1.49)	(1.74)
Market beta	0.0027	-0.0061	-0.1469	-0.0193
	(0.32)	(0.59)	(1.39)	(0.62)
Time fixed effects	Yes	Yes	Yes	Yes
Style fixed effects	Yes	Yes	Yes	Yes
R^2	0.34	0.10	0.08	0.07
N	15,616	15,616	2,809	2,809

This table shows determinants of foreign currency derivatives (FCD). The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. In columns (1) and (2) probit regressions are carried out. Columns (3) and (4) show the results of a panel regression. The dependent variable in columns (1) and (2) is the FCD dummy. In column (3) (column (4)) the dependent variable is FCD gross weight (changes in FCD gross weight). Performance (beta) is the intercept (slope on the international market index) from the international Fama and French (1993) 3-factor model calculated for each quarter using daily net fund returns. FCD engagement is a dummy variable set to one when a fund uses foreign currency derivatives in the respective quarter and zero otherwise. FCD weight (change) is the gross weight (change) of all FCD in the respective quarter. FX holdings (change) is the (change in) fraction of TNA invested into foreign currencies not counting FCD holdings. In Panel (1) and (2) explanatory variables are standardized and lagged one period. R^2 is McFadden's pseudo R^2 (adjusted R^2) in columns (1) and (2) (columns (3) and (4)). ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values, given in parentheses, are based on standard errors clustered by fund in in columns (1) and (2), and based on standard errors 2-dimensionally clustered by fund and quarter following Petersen (2009) in columns (3) and (4).

Table 9
FX exposure of long-short portfolio based on foreign currency derivatives engagement

	FX index value			FX index changes		
	Nonusers	User	Long-short Portfolio	Nonusers	User	Long-short Portfolio
Panel A: Broad Nominal Dollar Index						
FX index	-1.2211***	-1.1713***	0.0499***	-0.7945***	-0.7582***	0.0363***
	(-4.55)	(-4.48)	(2.99)	(-3.72)	(-3.66)	(2.71)
Intercept	0.0039	0.0032	-0.0007***	0.0043	0.0037	-0.0007***
	(1.16)	(0.98)	(-2.72)	(1.24)	(1.07)	(-2.70)
Adj. R^2	0.16	0.16	0.05	0.09	0.09	0.04
N	191	191	191	189	189	189
Panel B: Major Nominal Dollar Index						
FX index	-2.8671***	-2.7786***	0.0885***	-1.6046***	-1.5474***	0.0572**
	(-8.05)	(-8.21)	(2.98)	(-3.22)	(-3.24)	(2.00)
Intercept	0.0025	0.0018	-0.0006**	0.0044	0.0037	-0.0007***
	(0.80)	(0.60)	(-2.52)	(1.27)	(1.10)	(-2.70)
Adj. R^2	0.31	0.30	0.06	0.12	0.11	0.03
N	191	191	191	189	189	189

This table shows results of a regression of portfolios sorted by their foreign currency derivatives (FCD) engagement on US Dollar strength. The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. At the end of each month *t*, funds are sorted into the long (short) portfolio based on their engagement (nonuse) of FCD. In Panel A, portfolio net returns are regressed on the Broad Nominal Dollar Index from the Federal Reserve. In Panel B, the Major Nominal Dollar Index from the Federal Reserve is used. ***, **, * denote 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.

Table 10
Performance and risk regression – Alternative explanations

	Panel A: Dimson		Panel B: Gross returns		Panel C: Non-using		Panel D: Global benchmark factors	
	Alpha	Beta	Alpha	Beta	Alpha	Beta	Alpha	Beta
Light	0.0004	-0.0038	-0.0005*	0.0007	-0.0006*	0.0004	-0.0003	-0.0010
	(0.81)	(-0.45)	(-1.75)	(0.10)	(-1.81)	(0.05)	(-0.98)	(-0.13)
Heavy	0.0001	-0.0255**	-0.0002	-0.0193**	-0.0002	-0.0196**	-0.0001	-0.0288**
	(0.17)	(-2.42)	(-0.58)	(-2.38)	(-0.72)	(-2.23)	(-0.31)	(-2.51)
Non-using					-0.0002	-0.0008		
					(-0.76)	(-0.12)		
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	0.77	0.47	0.56	0.43	0.56	0.43	0.53	0.61
N	17,390	17,390	17,390	17,390	17,390	17,390	17,390	17,390

This table shows results of a panel regression of fund performance and risk on FCD use. The sample consists of actively managed international equity funds from Morningstar and the CRSP mutual fund database over the period 1999-2014. Alpha (beta) is the intercept (slope on the international market index) from the international Fama and French (1993) 3-factor model. Performance and risk are calculated for each fund and quarter individually using daily fund net returns. In Panel A, regressions are carried out using Dimson's (1979) approach. In Panel B, regressions are carried out using fund gross returns. In Panel D, the global Fama and French (1993) 3-factor model including the US in the factors is used. $Light_{i,t-1}$ ($Heavy_{i,t-1}$) is a dummy variable equal to one when a fund has FCD investments below (above) the median, measured by gross holdings weight in the respective quarter and zero otherwise. ***, **, * denote significance of the coefficient at the 1%, 5% and 10% level, respectively. T-values based on standard errors 2-dimensionally clustered by fund and quarter following Petersen (2009) are given in parentheses.

VII. Conclusion and outlook

This dissertation contributes to an increasingly relevant field of finance. By presenting convincing evidence on how different mutual funds employ derivatives and other complex instruments, it fills a significant gap in the literature. This dissertation shows that actively managed domestic US equity funds successfully employ options and futures. Option users have a higher performance and lower systematic risk, compared to their non-using peers. This is also true when controlling for the possible outperformance of common option strategies presented in this dissertation's third article. Furthermore, domestic equity mutual funds also mitigate most of the adverse influence of investor in- and outflows on their performance when employing derivatives. Bond funds, on the other hand, do not benefit from their use of complex instruments. Complex instruments permission to use and the actual use of most complex instruments do not affect bond funds' performance and risk characteristics. Only interest rate futures influence performance and risk of bond mutual funds. Users of interest rate futures perform worse than their non-using peers and take on higher interest rate risk by increasing their portfolio durations. Regarding the use of foreign currency derivatives to manage investments in foreign countries, international equity funds hedge their foreign currency exposure leading to lower foreign market risk but not to increased fund performance.

Thus, investors, researchers and regulators need to take complex instruments, especially derivatives into account when assessing mutual funds' performance and risk. This is highlighted by a new rule to govern derivatives use of mutual funds proposed by the US Securities and Exchange Commission (SEC) at the end of 2015.[1] The call for comments of the SEC also emphasizes the need for further research in this area. First, the performance assessment of bond and international mutual funds employing derivatives would benefit from

[1] See the SEC's press release at https://www.sec.gov/news/pressrelease/2015-276.html accessed 2016/02/24.

an investable derivative strategy benchmark factor, similar to the investable option strategy factor for domestic equity funds, proposed by the second article of this dissertation.

Second, future research should combine information on regulatory data from mutual funds' SEC filings with derivatives holding information from Morningstar to gain further insights into how mutual funds employ derivatives and which strategies they follow. The second article of this dissertation clearly shows that equity mutual funds mainly use protective puts and covered call strategies. If protective put strategies are used to hedge against adverse movements of the market or of individual stocks needs to be analyzed. Furthermore, income generation via covered calls may also be carried out for index or individual options. If and how funds time these strategies may also provide new insights into how funds invest into derivatives.

This dissertation's fourth paper presents results on bond funds using interest rate futures to increase their portfolio duration. Unfortunately, data on other interest rate derivatives, such as swaps, caps, floors, and swaptions is not available from the SEC. Nevertheless, using bond fund holdings data, these derivatives could be identified and their relation to fund performance and risk may be investigated to get a clearer picture of bond fund interest rate derivatives use.

The analysis of foreign currency derivatives in international funds, presented in article five of this dissertation, also offers ideas for future research. Instead of the aggregated analysis carried out here, future research should investigate fund's exposure to individual foreign markets and currencies. Moreover, international funds may use derivatives to implement country timing or carry trade strategies. How successful derivative user funds are in this regard compared to their nonusing peers, is another interesting research question.

Fourth, the investigation of other fund types also seems worthwhile. Balanced and hybrid funds, i.e. funds investing in both stocks and bonds (e.g., Comer et al., 2009), may use derivatives in an overlay management framework for their strategical and tactical asset allocation decisions. Future research may investigate how these overlay structures are used and how they influence market timing results. According to Deli et al. (2015), alternative investment funds, i.e. funds seeking to provide low correlations to traditional stock and bond indices, are more likely to invest heavily in derivatives. Hence, they may have more expertise in this area. To test this suggestion, the derivatives use of this founds should also be tested empirically.

In conclusion, this dissertation makes a contribution to the research of derivatives use by mutual funds in different aspects. However, there are still many open research questions to consider in future research.

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