Institute of Insurance Economics

University of St.Gallen

ASSET PRICING AND EXTREME EVENT RISK: COMMON FACTORS IN ILS FUND RETURNS

SEMIR BEN AMMAR

WORKING PAPERS ON RISK MANAGEMENT AND INSURANCE NO. 175

EDITED BY HATO SCHMEISER

CHAIR FOR RISK MANAGEMENT AND INSURANCE

NOVEMBER 2016

Asset Pricing and Extreme Event Risk: Common Factors in ILS Fund Returns

Semir Ben Ammar*, Alexander Braun, and Martin Eling

November 2016

Abstract

Alternative investment funds focusing on insurance-linked securities (ILS) exhibit a unique behavior. We introduce four new factor models, which explain their return characteristics. Despite a strong overall fit, we are left with significantly positive alphas for about one quarter of our sample. Some of these abnormal returns can be attributed to beta exposures associated with non-cat-bond ILS. In addition, they are related to fund size, fund age, and performance fees. Finally, we do not find evidence for market timing abilities but can rule out pure luck by controlling for false discoveries.

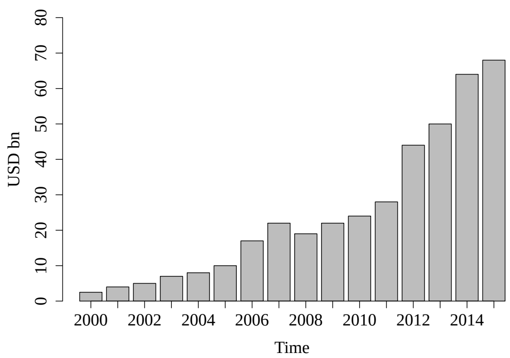
Key words: Insurance-Linked Securities · Investment Funds · Factor Model · Catastophe Bonds
JEL Classification: G13 · G22

*Semir Ben Ammar (semir.benammar@unisg.ch), Alexander Braun (alexander.braun@unisg.ch), and Martin Eling (martin.eling@unisg.ch) are with the Institute of Insurance Economics, University of St. Gallen, Tannenstrasse 19, CH-9000 St. Gallen. Phone: +41 71 224 7994.

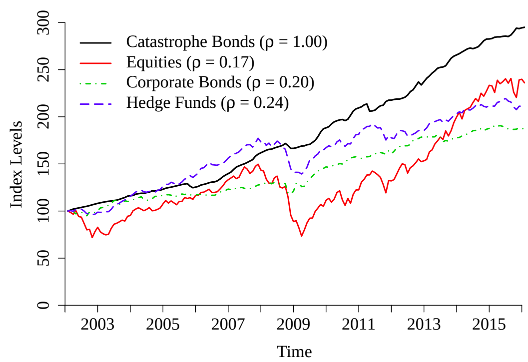
1 Introduction

Over the last two decades, a new asset class called insurance-linked securities (ILS) has emerged. Its dominant representative is the catastrophe (cat) bond, a financial instrument that pays regular coupons unless a disaster occurs during the contract term, leading to full or partial loss of principal. Cat bonds have been developed by (re)insurance companies as a hedge against extreme event exposure in their property risk portfolios (see, e.g., Swiss Re, 2006). They typically cover natural perils such as windstorms and earthquakes in various regions around the world and may be triggered either through insurance losses or physical parameter measurements in excess of a threshold.[1] The market for cat bonds and other ILS has witnessed substantial growth rates in the recent past (see Figure 1(a)). Its popularity among investors, particularly in the current low interest rate environment, is based on high single-digit returns that are stable and largely uncorrelated with the wider capital markets (see Figure 1(b)). Such instruments may thus be considered a genuine alternative asset class. However, direct investments in ILS require a lot of specific expertise (see, e.g., Braun et al., 2013). Another method to gain exposure is through open-end funds. Although the latter are sometimes still lumped together with mutual funds or hedge funds in the fixed-income space, their returns exhibit a unique behavior.[2]

Figure 1: Evolution of the ILS asset class



(a) ILS market volume



(b) Cat bond performance vs. other asset classes

Subfigure (a) illustrates the development of the market volume in insurance-linked securities from January 2000 to December 2015. Market volume includes catastrophe bonds, sidecars, industry loss warranties (ILW), and collateralized reinsurance. *Source:* AON Benfield (2013, 2016). Subfigure (b) illustrates the development of catastrophe bonds and other asset classes from January 2002 to December 2015. The following total return indices are used: Swiss Re Global Cat Bond Performance Index (cat bonds), S&P 500 Performance Index (equities), Barclays Investment Grade Corporate Bond Index (corporate bonds), HFRI Fund Weighted Composite Index (hedge funds). Pairwise return correlations with the Swiss Re Global Cat Bond Performance Index are denoted by ρ. The average annual return and volatility of the latter over the considered time period amounted to 7.8% and 2.6%, respectively.

[1] For a detailed explanation of the structural features of cat bonds see, e.g., Braun (2016).

[2] A distinct characteristic of hedge funds is their ability to employ sophisticated strategies (e.g., short selling, leverage, and derivatives). Yet, the majority of their kind trades in traditional asset classes such as equities and fixed income. ILS funds, in contrast, distinguish themselves by focusing their activities on the market for investable insurance risk.

Consequently, classical factor models should not be suitable to analyze the behavior of dedicated ILS funds. Existing empirical research, however, mainly focuses on explaining the risk spread of the underlying securities themselves (see, e.g., Galeotti et al., 2013; Braun, 2016; Gürtler et al., 2016) as well as their risk implications (see Hagendorff et al., 2013, 2014). A specific factor model for the returns of diversified ILS portfolios has not been suggested yet. Given the abundance of the asset pricing literature, this is quite astonishing. In the wake of the pioneering work of Sharpe (1964, 1992) and Fama and French (1992, 1993), several authors began to employ factor models for both style analysis and performance measurement purposes. Blake et al. (1993), e.g., applied the asset-class factor model idea of Sharpe (1992) to bond mutual funds. Carhart (1997) added a momentum factor to the classical three-factor model of Fama and French (1992) and analyzed the persistence of equity mutual fund returns. Furthermore, Fung and Hsieh (1997) extended the setup of Sharpe (1992) beyond mutual funds to account for dynamic trading strategies of hedge fund managers. Based on their earlier insights, Fung and Hsieh (2004) derived a comprehensive risk-factor approach to explain the returns of diversified hedge fund portfolios. More recently, Sadka (2010) added a liquidity risk factor for hedge funds, Chen et al. (2010) controlled for several sources of nonlinearity to evaluate the timing ability of fixed-income managers, and Ammann et al. (2010) developed a model that accounts for the particularities of convertible bond funds.

Regardless of the impressive historical performance and substantial diversification potential offered by ILS funds (see Figure 1), little is known about their return drivers to date. The paper at hand aims to fill this gap. Our contribution is threefold. First, we analyze the asset class' risk-return profile for the period from January 2002 to December 2015 relative to corporate bonds and hedge funds, with which it is often confounded. For this purpose, we collated a large dataset that covers the known universe of existing and terminated ILS funds. Second, we demonstrate the inability of traditional factor models to explain the time-series and cross-sectional return characteristics of ILS funds. Subsequently, we introduce four new approaches to address this issue: a single-index, a ratings-based two-factor, a perils-based three-factor, and a spread-based four-factor model. Third, we draw on these models to determine whether certain ILS funds were able to outperform their peers on a risk-adjusted basis in the past and attempt to identify the drivers of abnormal returns.

Our results indicate a superior historical performance of ILS funds compared to other asset classes according. In addition, they delivered positive returns in 89% of all analyzed months. This figure compares to a mere 66% for hedge funds and 71% for corporate bonds. While all traditional factor models fail miserably, our new approaches are found to explain the time series of ILS fund returns with adjusted R-squareds of around 70%. The latter further increase to 80% when controlling for a single extreme outlier caused by Hurricane Katrina in August 2005. Based on the cross-sectional analysis, we can single out the perils-based model as the strictest benchmark for ILS funds. Given its properties, it should be well suited for style analysis and performance measurement in this rapidly growing market. The perils model leaves significantly positive alphas for about one quarter of all funds. It is possible to attribute some of these abnormal returns to beta exposures associated with non-cat-bond ILS. Furthermore, they are related to fund size, fund age, and performance fees. Finally, we do not find evidence for market timing abilities but can rule out pure luck by controlling for false discoveries.

The remainder of this paper is organized as follows. In Section 2, we describe how our sample of ILS funds has been compiled and discuss various potential return biases, including their relevance in our context. The (classical and new) factor models that form the center of our analysis are then introduced in Section 3. Section 4 includes the empirical results, i.e., the historical performance of ILS funds, the capability of the different factor models to fit the funds' return time series, and an assessment of their explanatory power with regard to the cross section of expected excess returns. In addition, we test the robustness of our results for various subperiods, subindices, and an alternative ILS fund portfolio. Finally, in Section 5 we present our conclusions.

2 Dedicated ILS funds

2.1 Sample selection

We composed our dataset by identifying and cross-checking all live and terminated ILS funds in the the Artemis Deal Directory, on Insurancelinked.com, in press releases, on industry websites, and in the Morningstar CISDM database. For each fund, we retrieved monthly net-of-fee total return data from Bloomberg. Moreover, we collected information about the current assets under management (AuM), expense ratios, front and back loadings, performance fees, top ten holdings, and cash reserves. In case these figures were unavailable on Bloomberg, we searched for them through various Internet sources, term sheets, and prospectuses. For some funds that do not publish returns at all, it was possible to obtain data directly from the managers.[3] We controlled for any duplicates listed under different names and, whenever available, chose the institutional share class quoted in U.S. dollars. The number of funds identified totals 57, with return data starting in January 2001 and ending in December 2015.[4]

Table 1 shows the funds' characteristics on an aggregate level ("All Funds") as well as separately for the Bloomberg categories "Alternative" and "Fixed Income." The categories "Equity", "Mixed Allocation", "Specialty", and funds without any classification have been subsumed under "Other".[5] Although this is a very broad categorization, it allows for an aggregation and enables us to check whether the Bloomberg label is somehow related to the risk-return profile of the funds. Yet, as stressed by Fung and Hsieh (1997), the actions of fund managers do not necessarily correspond to their stated intentions. Hence, the true investment style can only be assessed by means of a return decomposition with suitable factor models.[6] In addition to the aforementioned categorization, we separately report the characteristics for surviving funds ("Live") and acquired or dissolved funds ("Dead"). Based on the latest AuM of

[3] It should be noted that one fund (Fermat Capital) that we know of, refrained from providing return information for our study. Furthermore, there are no funds of funds in our sample.

[4] Although, we possess pre-2002 return data for some of the funds, none of the time series for the ILS-specific factors dates that far back. Thus, we needed to select January 2002 as the starting point for our regression analyses.

[5] A special Bloomberg category for ILS funds does not exist. At first glance, the classifications "Fixed Income" and "Alternative" may appear reasonable due to the bond format of many ILS as well as the nonstandard risk exposure. However, as will be shown in the fourth section, the return characteristics of ILS funds differ substantially from those of typical bond mutual funds and hedge funds. The classification "Equity" may have been chosen as certain instruments in the ILS investment universe exhibit an equity-like character (e.g., the first-loss pieces in reinsurance sidecars).

[6] Deviations from the stated investment objectives of a fund are termed style drift (see, e.g., Cumming et al., 2009). This phenomenon is known to be of particular relevance for hedge funds and private equity funds.

the survivors in our sample, we size the ILS fund market at USD 21.80 billion in December 2015. This compares to a cat bond market of USD 25.96 billion at the end of 2015 (see Artemis Deal Directory). Swiss Re (2013) estimated 61% of the outstanding cat-bond volume to be held by dedicated ILS funds.[7] Assuming this fraction has been relatively stable in the meantime, we may infer that USD 15.84 billion (or 72.64%) of the ILS fund AuM in our sample are invested in cat bonds, leaving USD 5.97 billion (or 27.36%) in other ILS instruments. Consequently, factor models relying on cat bond performance indices should be well suited to explain ILS fund returns.

Table 1 shows that dead funds on average exhibited slightly higher expense ratios and load fees than surviving funds.[8] At the same time, they earned a lower performance fee of 5.45% p.a. compared to 7.33% p.a. for surviving funds, suggesting underperformance as a reason for failure. However, only the difference in the maximum load fees is statistically significant. On average, an ILS fund is approximately six years old, illustrating that this fast-growing part of the investment industry is still in its early phase.[9] Dead funds tend to discontinue their business after 3 $\frac{1}{2}$ years. Furthermore, surviving funds seem to exhibit a larger concentration on their top ten holdings than dead funds (39.99% vs. 33.67%) and keep substantially less cash (11.33% vs. 22.23%).

2.2 Potential return biases

Return data of mutual funds and particularly hedge funds may exhibit biases, which should be scrutinized for ILS funds as well. These include survivorship bias, backfilling bias, self-selection bias, and stale prices (see, e.g., Fung and Hsieh, 2000; Carhart et al., 2002; Getmansky et al., 2004; Agarwal et al., 2011). We have at least two indications that survivorship bias is less of an issue for us. First, Bloomberg does not delete the returns of defunct or acquired funds. Second, given the limited number of funds in the ILS universe, launches and terminations receive quite a bit of attention within the ILS community. Thus, media reports are a reliable means to keep track of the industry. Given the manageable size of the ILS market, we are convinced to have covered the known universe of live and dead funds.

Backfilling bias occurs, when funds join a database after an incubation period. Those with a good track record may decide to disclose their past returns, whereas poorly performing funds have an incentive to refrain from backfilling information. As a consequence, performance figures may be upward biased. However, the ILS funds in our sample exhibit a transparent history and, for all of them but one, we were able to obtain return time series starting at inception. Furthermore, we controlled for a potential backfilling bias by excluding the first 12 and 24 monthly returns for each fund. In contrast to the findings in the hedge fund literature, this even slightly increased the mean return of ILS funds. Hence, we may safely state that backfilling bias is not an issue in our empirical analysis.

Self-selection bias results from the general decision of a manager whether or not to report returns to

[7] The remaining volume is held by asset managers (17%), pension funds (14%), insurers (4%), hedge funds (3%), and reinsurers (1%).
[8] Note that fees could have decreased over time such that they now appear different for dead than for live funds.
[9] The average age of high yield bond funds between 1991 and 2010 was about 15 years (see Fang et al., 2014).

Table 1: Fund characteristics

Category	Time Period	# of Funds	Avg. AuM (USD millions)	Avg. Exp. Ratio (% p.a.)	Avg. Max. Load (Front and Back, % p.a.)	Avg. Performance Fee (% p.a.)	Avg. Fund Age (years)	Avg. Top 10 Holdings (% of AuM)	Avg. Cash holdings (% of AuM)
All Funds	01/2001–12/2015	57	428.99	1.69	1.42	6.92	5.45	39.50	13.33
By Fund Category									
Alternative	07/2002–12/2015	20	311.29	1.64	0.65	7.65	5.05	38.21	6.75
Fixed Income	06/2001–12/2015	15	543.39	1.79	2.53	2.86	5.89	43.60	11.42
Other	01/2001–12/2015	22	460.89	1.61	1.41	9.41	5.52	33.93	20.22
By Current Status									
Live Funds	01/2001–12/2015	45	506.85	1.69	1.12	7.33	5.97	39.99	11.33
Dead Funds	07/2002–10/2013	12	149.98	1.76	2.34	5.45	3.51	33.67	22.23

This table summarizes the characteristics of 57 ILS funds both aggregated ("All funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the number of funds in each category, the average assets under management (AuM), the average expense ratio, the average maximum loading based on the sum of back and front loadings if charged, the average performance fee if charged, the average fund age in years, the average top ten holdings as a share of total AuM, and the average cash holdings as a share of total AuM. Note that nine of the funds classified as "Other" neither exhibited a Bloomberg category nor offered additional information. All figures are based on the latest available date. The overall sample starts in January 2001 and ends in December 2015.

a database. It can only be large, if the performance of non-reporting funds differs substantially from that of their reporting counterparts. When compiling our sample, we checked various sources to identify all existing funds with major exposure to ILS. We then directly contacted those funds whose returns were not accessible through any of our data sources. Ultimately, only one of these known funds decided not to disclose any information at all and is thus missing in our sample (see footnote 3). Of course, we cannot entirely rule out the possibility that we missed a small number of minor funds, which neither reported their returns to any data provider nor attracted notable public attention. The same is true for funds that could not be identified as part of the industry, since their managers never explicitly expressed the intention to invest in ILS. Taken together, however, these indications are too weak to substantiate the suspicion of self-selection bias.

Another source of bias may be stale prices, which typically occur due to illiquid exposures in the portfolio of the funds and lead to serially correlated returns (see, e.g., Getmansky et al., 2004). If present, this issue makes reported returns appear smoother than latent economic returns. As a consequence, correlations, risk measures, and performance indicators will be misleading and may cause erroneous investor decisions. Yet, this should be a lesser problem in the case of ILS funds, because we found a large fraction of the AuM to be invested in cat bonds. For the latter, a relatively liquid secondary market exists (see, e.g., Braun, 2016).[10] Therefore, pricing indications are available on a weekly or even daily basis, limiting the problem to less liquid ILS types such as collateralized reinsurance. Hence, we do not see the necessity to unsmooth the ILS fund return time series in our sample with econometric techniques such as the one introduced by Getmansky et al. (2004).[11]

3 Factor models

3.1 Traditional approaches

First of all, we run a simple asset-class factor model in the style of Sharpe (1992), which can be employed to reveal a fund's passive exposure to various asset classes. We include a factor for equities, treasuries, corporate bonds, municipal bonds, mortgage-backed securities, convertible bonds, real estate, hedge funds, and commodities. The specific (total return) indices used in this regard have been summarized in Table 2. All factors are measured as monthly returns in excess of the one-month T-Bill rate.

[10] Despite this fact, cat bonds are certainly less-liquid than traditional assets such as stocks. Similar to corporate bonds, we may therefore expect an illiquidity premium to be present (see Bao et al., 2016). Throughout the following empirical analyses, the latter will be captured by a cat bond market factor in our asset pricing models. Owing to the scarcity of publicly available ILS data, a separation of the illiquidity premium from other components of the expected return is currently not possible.

[11] A related phenomenon is managed returns. Because of a hedge-fund like compensation structure, some ILS funds might be inclined to deliberately smooth or inflate their returns. Intra-year return smoothing is a means to minimize the number of negative months. More specifically, high positive returns can be underreported to create reserves that are subsequently used to offset negative returns or to boost the December results to earn a performance fee. However, the generally very low volatility of cat bond price quotes, as reflected by the Swiss Re Global Cat Bond Performance Index, poses little incentives for return smoothing (see Figure 1 (b)). Moreover, none of the return series in our sample exhibits the characteristic December spike often generated by hedge fund managers (see Agarwal et al., 2011).

Table 2: Asset-class factors

Factor	Measure	Mnemonic/Ticker
MSCI	MSCI World Index	MSWRLD$
TREASURY	Barclays U.S. Treasuries Index	LHUSTRY
CORPORATE	Barclays U.S. Corporate Bond Index	LHCCORP
MUNICIPAL	Barclays Municipal Bond Index	LHMUNIC
MORTGAGE	Barclays U.S. Mortgage-Backed Securities Index	LHMNBCK
CONVERTIBLE	Merrill Lynch All Convertible Index	MLCVXA0
REAL ESTATE	S&P Case/Shiller Composite-20 Home Price Index	SPCS20 Index
HEDGE FUNDS	HFRI Fund Weighted Composite Index	HFRIFWI Index
COMMODITY	S&P Goldman Sachs Commodities Index	SPGSCITR Index

This table summarizes the factors for the asset class model in the sense of Sharpe (1992). The second column shows the indices through which the factors are measured and the third column includes the corresponding Datastream Mnemonics or Bloomberg Tickers. Each index has been used in its total return version. All factors are excess returns.

Subsequently, we run the Carhart (1997) model, which adds a momentum factor (MOM) to the three classical variables equity-market (MKTRF), small-minus-big capitalization stocks (SMB), and high-minus-low book-to-market stocks (HML), as coined by Fama and French (1993). SMB, HML, and MOM have been downloaded from Kenneth French's data library. MKTRF is the total return of the MSCI World in excess of the one-month T-Bill rate.

Finally, we focus on specific fixed-income and hedge-fund factor models that have been proposed in the literature. This is because ILS funds are often classified into either one of these two categories. Fama and French (1993) as well as Blake et al. (1993) are well-known approaches with bond-specific factors. The former extend their earlier equity model by a factor for the term premium (TERM) and the default risk premium (DEF). We capture TERM through the monthly return on the Barclays U.S. Long-Term Government Bond Index in excess of the one-month T-Bill rate and DEF as the difference between the monthly returns on the Barclays U.S. Long-Term Corporate Bond Index and the Barclays U.S. Long-Term Government Bond Index. Similar to Fama and French (1993), Blake et al. (1993) rely on TERM, which they combine with a high-yield bond index (HYIELD) and a mortgage-backed securities index (MORTGAGE). With regard to the latter, refer to Table 2. HYIELD will be represented by the Barclays Global High Yield Index. All indices have been downloaded in their total return version.[12]

From the hedge fund literature, we adopt the seven-factor approach of Fung and Hsieh (2004), which comprises all factors ofFama and French (1993) except HML, plus three trend-following factors for bonds (PTFSBD), exchange rates (PTFSFX), and commodities (PTFSCOM). In contrast to Fung and Hsieh (2004), we measure TERM and DEF in excess returns instead of yields.[13] The hedge-fund-specific factors PTFSBD, PTFSFX, and PTFSCOM have been retrieved from the website of David Hsieh.

[12]The respective Datastream Mnemonics are: Barclays U.S. Long-Term Government Bond Index: LHGOVLG; Barclays U.S. Long-Term Corporate Bond Index: LHCCRLG; Barclays Global High Yield Index: LHMGHYD.

[13]This has been suggested by Sadka (2010) and ensures that alpha can be interpreted as an excess return as well.

3.2 New ILS-specific factor models

We begin with a single-factor approach in the spirit of the classical capital asset pricing model (CAPM), which will be termed *CAT-CAPM* and is formally defined as:

$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKT_t + \epsilon_{i,t}, \tag{1}$$

where $CATMKT_t$ and $R^e_{i,t}$ denote the returns on the cat bond market and the ILS fund, respectively, both in excess of the one-month T-Bill rate. We proxy the factor CATMKT by means of the Swiss Re Global Cat Bond Index [Bloomberg ticker: SRGLTRR], which tracks the performance of all USD- and EUR-denominated cat bonds independent of ratings, reference perils, and trigger types. If ILS funds exclusively pursue a by-and-hold strategy in a diversified cat bond portfolio, this model should be sufficient to explain their excess returns over time.

In addition, we propose a *ratings-based model*, which is constructed as follows:

$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKO_t + \beta_{i,2} BBCAT_t + \epsilon_{i,t}. \tag{2}$$

$BBCAT_t$ is defined as the excess return over the one-month T-Bill rate on the Swiss Re BB Cat Bond Index [Bloomberg ticker: SRBBTRR], which captures the performance of all outstanding cat bonds with a BB rating.[14] The variable $CATMKO_t$ equals the intercept plus the residuals of a regression of $CATMKT_t$ on $BBCAT_t$. In creating CATMKO, we follow Fama and French (1993), who suggest orthogonalizing the market factor, if it shares a large degree of variance with the additional regressors. This is particularly relevant here, because the vast majority of cat bonds is issued with a BB rating (see, e.g., Braun, 2016). The rotated market factor CATMKO thus captures the return variation of all outstanding cat bonds that exhibit a non-BB rating.

The next model will be termed *spread model*, because it rests on the insight that $BBCAT_t$ can be unfolded into different fixed-income risk drivers. More specifically, it should include a term premium, a default risk premium, and a potential insurance risk premium and can therefore be expressed as follows:

$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKO1_t + \beta_{i,2} TERM3Y_t + \beta_{i,3} DEFCORP_t + \beta_{i,4} DEFCAT_t + \epsilon_{i,t}, \tag{3}$$

where $TERM3Y_t$ is defined as the return on the Barclays 1-3 years U.S. Treasury Total Return Index [Datastream mnemonic: LHG13US] in excess of the one-month T-Bill rate. The maturity of cat bonds typically ranges between one and three years (see, e.g., Braun, 2016). Therefore, we decided to adjust the term premium factor accordingly. $DEFCORP_t$ equals the difference between the return on the Barclays 1-3 years U.S. High Yield Total Return Index [Datastream mnemonic: LHHY13B] and the Barclays 1-3 years U.S. Treasury Total Return Index. Again, we have ensured that the maturities of the index constituents match those that are usually found in the cat bond market. Moreover, $DEFCAT_t$ represents

[14] Apart from S&P and Fitch BB ratings, the index also includes the equivalent notch "Ba" of Moody's.

the return difference between the Swiss Re BB Cat Bond Index [Bloomberg ticker: SRBBTRR] and the Barclays 1-3 years U.S. High Yield Total Return Index. This factor is particularly interesting, since the existence of a cat-bond return premium above comparably-rated corporate debt has regularly been conjectured among industry practitioners (see, e.g., RMS, 2012). Anecdotal evidence for this notion dates back to the early days of the ILS market when it was known as "novelty premium" (see, e.g., Bantwal and Kunreuther, 2000). More recently, however, empirical research showed that the yield spreads of cat bonds did not exceed those of corporate bonds at all times (see, e.g., Partner Re, 2015; Braun, 2016). This is in line with theoretical reasoning; in the absence of arbitrage, instruments with the same rating and maturity should not offer different returns. Hence, by testing whether the factor DEFCAT is priced, it is possible to shed light on the question of whether a premium for the esoteric nature of catastrophe risk (still) exists. Finally, $CATMKO1_t$ is the excess return on the market portfolio that has been orthogonalized on $TERM3Y_t$, $DEFCORP_t$, and $DEFCAT_t$. Hence, the factor CATMKO1 summarizes the return variation of all outstanding cat bonds that is not attributable to the considered risk premiums.

The last approach that we introduce is a three-factor *perils model* of the form:

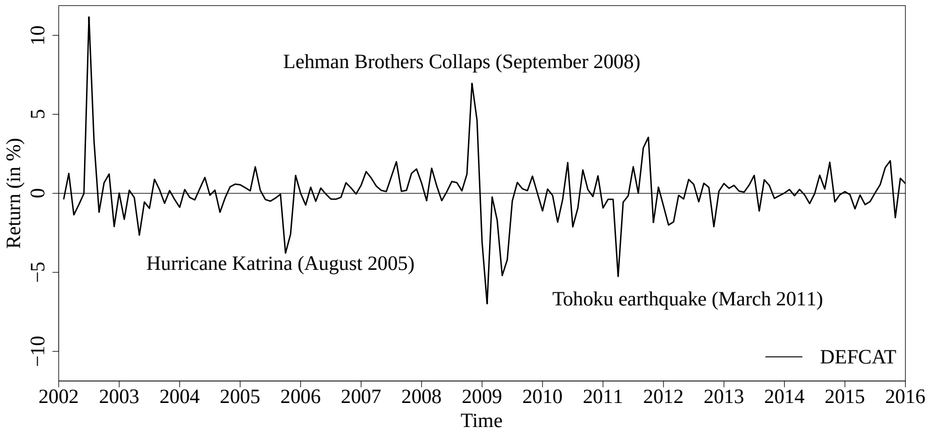
$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKO2_t + \beta_{i,2} USHU_t + \beta_{i,3} USEQ_t + \epsilon_{i,t}, \tag{4}$$

where $USHU_t$ and $USEQ_t$ are the returns on the Swiss Re U.S. Wind Cat Bond Index [Bloomberg ticker: SRUSWTRR] and the Aon Benfield U.S. Earthquake Bond Index [Bloomberg ticker: AONCUSEQ], respectively, both in excess of the one-month T-Bill rate. These indices track the performance of all single-peril U.S. wind and earthquake cat bonds. $CATMKO2_t$ is the excess return of the cat bond market orthogonalized on $USHU_t$ and $USEQ_t$ and therefore represents the variation in the market returns that is not driven by single-peril U.S. wind and earthquake risk. In other words, it captures all multi-peril bonds (U.S. and non-U.S.) as well as non-U.S. single-peril bonds.[15] This model should be suitable for style analysis, i.e., it can reveal in which specific types of natural catastrophe risk an ILS fund invests.

Table 2 summarizes the statistical properties of the factors for the time period between January 2002 and December 2015. The average monthly return of DEFCAT (0.05) is not significantly different from zero. Therefore, an additional return premium for the nontraditional nature of insurance risk does not seem to be present (see Figure 2). In other words, over the considered time period, cat bonds exhibited the same expected excess return as similarly-rated corporate bonds. This is a surprising result, given that the issuance spreads of the former regularly exceed those of the latter (see, e.g., Swiss Re, 2016).

[15] It would certainly be insightful to add a U.S. multi-peril cat bond index to the model. In this case, the cat risk in a fund's portfolio could be identified even more precisely and the orthogonalized market factor would simply capture all non-U.S. perils. Unfortunately, data for such an index is currently not available.

Figure 2: Evolution of DEFCAT over time



This figure illustrates the time series of the DEFCAT factor, i.e., the excess return of BB-rated cat bonds over BB-rated corporate bonds between January 2002 and December 2015. Despite a few spikes, the overall mean is not significantly different from zero.

The means of all other factors in Table 3 are significantly positive. Comparing TERM3Y and DEFCORP, we notice that the default risk premium (0.30) is three times larger than the term premium (0.10). The *ratings model* summarizes all three elements (TERM3Y, DEFCORP, and DEFCAT) in the average monthly return of BBCAT (0.45). The remaining contribution in the *ratings model* and the *spread model* equals 0.18 (see CATMKO and CATMKO1), which captures general market volatility as well as any other risk drivers. Turning to the *perils model*, we notice that the risk premiums for both single-peril U.S. hurricane (0.63) and U.S. earthquake exposures (0.40) are much higher than for the hodgepodge of perils inherent in CATMKO2 (0.12). This is consistent with earlier empirical evidence for an excess spread on transactions that cover so-called peak territories such as the U.S., which are abundant in the cat bond market (see, e.g., Braun, 2016).[16] Table 3 shows the correlation matrix for the ILS-specific factors. Apart from the fact that the orthogonalized market factor improves the interpretability of the multi-factor models, this step is also a statistical necessity, because the excess returns on the cat bond market have a relatively high correlation with USHU and BBCAT. Based on these considerations, we may conclude that multicollinearity is not an issue for the suggested factor model specifications.

[16] Transactions for nonpeak territories, in contrast, are a relatively rare and sought-after means for the diversification of ILS portfolios. Accordingly, they command significantly lower issuance spreads (see, e.g., Braun, 2016).

Table 3: New ILS-specific factors

(monthly)	Mean (in %)	Volatility (in %)	t-stat.	Median (in %)	Min. (in %)	Max. (in %)	Skewness	Kurtosis	Obs.
CATMKT	0.54	0.75	7.11***	0.50	–3.57	2.73	–1.32	10.08	168
CATMKO	0.18	0.21	8.62***	0.14	–0.66	0.98	0.28	5.66	168
BBCAT	0.45	0.88	4.93***	0.42	–4.90	2.99	–2.37	15.61	168
CATMKO1	0.18	0.21	8.81***	0.14	–0.65	0.96	0.26	5.55	168
TERM3Y	0.10	0.39	2.81***	0.08	–1.09	1.53	0.40	5.04	168
DEFCORP	0.30	1.84	1.71*	0.44	–11.31	7.59	–2.27	19.13	168
DEFCAT	0.05	1.73	0.30	0.09	–6.98	11.16	1.21	15.67	168
CATMKO2	0.12	0.48	2.88***	0.17	–3.52	1.13	–3.97	27.04	168
USHU	0.63	0.94	6.66***	0.39	–2.17	4.45	0.86	5.90	168
USEQ	0.40	0.56	7.81***	0.40	–5.83	1.46	–8.18	91.58	168

This table reports the mean, volatility, median, minimum, maximum, skewness, and kurtosis of the monthly excess return time series for the factors that enter the new ILS-specific models. It also includes t-statistics, using Newey and West (1987) robust standard errors with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The last column reports the number of observations. All time series start in January 2002 and end in December 2015.

Table 4: Correlation matrix

01/2002–12/2015	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) CATMKT	1.00									
(2) CATMKO	0.28	1.00								
(3) BBCAT	0.96	0.00	1.00							
(4) CATMKO1	0.28	0.99	0.00	1.00						
(5) TERM3Y	0.04	-0.12	0.08	0.00	1.00					
(6) DEFCORP	0.23	0.14	0.19	0.00	-0.44	1.00				
(7) DEFCAT	0.24	-0.12	0.29	0.00	0.28	-0.86	1.00			
(8) CATMKO2	0.64	0.08	0.65	0.09	0.08	0.08	0.22	1.00		
(9) USHU	0.76	0.32	0.69	0.32	0.00	0.19	0.15	0.00	1.00	
(10) USEQ	0.38	0.02	0.39	-0.01	-0.05	0.28	-0.09	0.00	0.34	1.00

4 Empirical results

4.1 Descriptive statistics

We construct equally-weighted indices for all funds, live and dead ones, as well as for each Bloomberg category.[17] Table 5 summarizes the return characteristics of these indices. For comparison purposes, it additionally includes results for the commercially-published EurekaHedge ILS Advisers Index (also equally-weighted), as well as a popular hedge fund and corporate bond benchmark. Over the last 15 years, ILS funds have earned an average annual return of 5.64% with a corresponding volatility of 2.26%. The lowest return (–3.46%) occurred in the aftermath of the Tohoku earthquake off the coast of Japan in March 2011. We observe a slightly lower mean return for dead funds and for the Bloomberg category "Fixed Income" that is typically perceived to be less risky. The ILS Advisers Index shows a higher average annual return of 6.31% and a lower volatility of 1.60%. These figures, however, must be viewed in light of the fact that this benchmark commands a shorter time series and merely comprises 32 constituents. It also does not capture defunct funds, leading us to suspect survivorship bias. We thus consider our own index to be a superior basis for performance measurement. Over the same time period, corporate bonds yielded an average annual return of 7.51%, but their return volatility of 8.20% was more than three times as high as for ILS funds. They also experienced a considerably larger negative minimum return of –15.13%. Finally, hedge funds, as which some ILS funds are classified, achieved a similar average annual return of 5.41%. However, they did so at the expense of a much higher volatility (5.98%) and a more negative minimum return (–6.84%).

Table 6 displays additional risk characteristics of the equally-weighted ILS fund indices as well as the hedge fund and corporate bond benchmarks. We show these because ILS may exhibit rare but very severe negative returns. Hence, the classical volatility is less suited as a risk measure for this asset class. Examining the semi-standard deviation (1.49%) and the 99.5 percent value-at-risk (1.05%), however, we again observe a much lower result compared to corporate bonds or hedge funds. Even the maximum drawdown from peak to trough merely amounts to 6.98%. Consequently, common financial performance measures, such as the Sharpe Ratio, the Sortino Ratio, the Excess Return on VaR, and the Calmar Ratio, also shown in Table 6, look much more favorable for ILS funds. Clearly, these results must raise some suspicion. The reason for such an odd risk profile is an empirical rather than a theoretical one. Most ILS securitize extreme-event insurance risk, i.e., natural disasters with recurrence periods of 200, 500, or even 1000 years (see, e.g., Smolka, 2006; Swiss Re, 2010). Against this background, a performance history of 15 years is short. In fact, the substantial drawdowns that are to be expected following a true mega event are much larger than anything that has been observed to date. This is a crucial aspect when analyzing the performance of ILS and a major reason for the fact that many industry professionals construct their portfolios based on forward-looking risk analyses by the specialized modelling firms RMS, AIR, and Core Logic (EQECAT). Historical performance figures as shown in this section should generally be interpreted with caution.

[17] Due to the absence of time series data on fund AuM, it is not possible to construct value-weighted indices.

Table 5: Return characteristics

Classification	Time Period	Obs.	Mean Return (% p.a.)	Median (% p.a.)	Min. (% monthly return)	Max. (% monthly return)	Volatility (p.a.)	Skewness	Kurtosis
All ILS funds	01/2001–12/2015	180	5.64	6.40	–3.46	2.12	2.26	–2.61	14.97
By Fund Category									
Alternative	07/2002–12/2015	162	5.97	6.37	–4.07	1.89	2.42	–2.41	15.47
Fixed Income	06/2001–12/2015	175	4.52	4.63	–4.28	1.54	1.95	–3.98	30.66
Other	01/2001–12/2015	180	6.08	7.12	–5.30	2.86	3.29	–2.95	17.34
By Current Status									
Live Funds	01/2001–12/2015	180	5.83	6.51	–3.53	2.23	2.45	–2.75	15.20
Dead Funds	07/2002–10/2013	136	4.89	5.76	–2.99	1.86	2.23	–2.01	10.29
Comparison Indices									
ILS Advisers Index	01/2006–12/2015	120	6.31	6.60	–3.94	1.60	2.07	–3.51	27.44
Hedge Fund Index	01/2001–12/2015	180	5.41	7.71	–6.84	5.15	5.98	–0.83	4.95
Corporate Bond Index	01/2001–12/2015	180	7.51	11.32	–15.13	7.59	8.20	–1.90	14.64

This table summarizes the return characteristics of 57 ILS funds both aggregated ("All ILS funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the number of time-series observations, the annualized mean return, annualized median return, the monthly minimum return, the monthly maximum return, the annualized volatility, the skewness, and the kurtosis. The table also shows benchmark indices for corporate bonds (Merrill Lynch BB corporate bond performance index) and hedge funds (HFRI Fund Weighted Composite Index) as a basis for comparisons. In addition, we included the EurekaHedge ILS Advisers Index, which comprises 32 constituents and was available for the time period January 2006 to December 2015. The overall sample starts in January 2001 and ends in December 2015.

Table 6: Risk and performance characteristics

Classification	Time Period	Downside-Volatility (p.a.)	VaR (% per month)	Max. Drawdown (in %)	Sharpe Ratio (p.a.)	Sortino Ratio (p.a.)	Excess return on VaR	Calmar Ratio (p.a.)	% of positive months
All ILS funds	01/2001–12/2015	1.49	1.05	6.98	1.86	2.81	0.33	0.60	88.89
By Fund Category									
Alternative	07/2002–12/2015	1.51	1.13	4.07	1.94	3.12	0.35	1.16	88.89
Fixed Income	06/2001–12/2015	1.39	0.93	4.28	1.63	2.28	0.28	0.74	92.00
Other	01/2001–12/2015	2.40	1.71	15.28	1.41	1.93	0.23	0.30	92.22
By Current Status									
Live Funds	01/2001–12/2015	1.67	1.17	8.79	1.79	2.62	0.31	0.50	90.56
Dead Funds	07/2002–10/2013	1.42	1.09	2.99	1.52	2.39	0.26	1.13	84.56
Comparison Indices									
ILS Advisers Index	01/2006–12/2015	1.32	0.87	3.94	2.51	3.95	0.50	1.32	93.33
Hedge Fund Index	01/2001–12/2015	3.88	3.57	21.42	0.66	1.02	0.09	0.19	65.56
Corporate Bond Index	01/2001–12/2015	5.78	4.89	25.13	0.74	1.05	0.10	0.24	71.11

This table summarizes risk and performance characteristics of 57 ILS funds both aggregated ("All ILS funds") and separated by Bloomberg category ("Alternative", "Fixed Income", or "Other") as well as status (i.e., "Live" or "Dead"). We report the time period, the annualized semi-standard deviation, the 99.5 percent value-at-risk (VaR) of the monthly series, the maximum drawdown, the annualized Sharpe ratio, the annualized Sortino ratio, the Excess Return on Value-at-Risk, the annualized Calmar ratio, and the percentage of positive monthly returns over the sample period. The table also shows benchmark indices for corporate bonds (Merrill Lynch BB corporate bond performance index) and hedge funds (HFRI Fund Weighted Composite Index) as a basis for comparisons. In addition, we included the EurekaHedge ILS Advisers Index, which was available for the time period January 2006 to December 2015. The overall sample starts in January 2001 and ends in December 2015.

4.2 Time-series regressions

Traditional factor models

Table 7 shows the coefficients for four asset-class models. To avoid collinearity that may arise due to the relatively high correlations of some of the fixed-income indices, we test the full model as well as three submodels with different factor combinations. The dependent variable is the aggregated ILS fund index in excess of the one-month T-Bill rate. Our first observation is the extremely low adjusted R-squared of not more than 0.02. Furthermore, we notice significant alphas of at least 0.30% per month. The full model does not result in any significant coefficients, whereas two submodels show some weak exposure towards hedge funds and convertible bonds. Table 8 contains the results for the traditional risk-factor models of Fama and French (1993), Blake et al. (1993), Carhart (1997), and Fung and Hsieh (1997). Once more, we find some mostly weak statistical significances and the adjusted R-squared does not exceed 0.03 with alphas remaining at the same level as in the case of the asset-class models in Table 7.

To control for statistical artifacts, we test the significant factors from Tables 7 and 8 in combination with the cat bond market factor CATMKT. The results of this analysis are shown in Table 9. Now the adjusted R-squared jumps to 0.67 and, apart from CATMKT, the coefficients of all independent variables, including the constant (alpha), become insignificant. We may thus conclude that traditional factor models are not suited to explain the time series of ILS fund returns.[18]

New ILS-specific factor models

Having demonstrated the failure of the traditional approaches, we now test our new ILS-specific factor models. Column (1) in Table 10 shows the *CAT-CAPM*. We observe a highly significant coefficient for CATMKT (market beta), an insignificant intercept, and an adjusted R-squared of 0.67. One reason for the market beta of 0.69 is that the diversified basket of cat bonds held by the funds in our equally-weighted index may differ from the market portfolio.[19] In addition, many funds are known to also invest in ILS other than cat bonds, such as collateralized reinsurance, industry loss warranties (ILWs), or extreme-mortality securitizations (see, e.g., AM Best, 2015). Columns (2) and (3) contain the results for the *ratings-based model* and the *spread model*, respectively. We find significant coefficients for all factors, paired with an insignificant intercept and an R-squared of 0.69. Therefore, ILS fund returns seem to be mainly driven by the variation of fixed-income risk premiums. Moreover, the results for the *perils model* are displayed in Column (4). This model is also associated with an adjusted R-squared of 0.69. The high coefficient for CATMKO2 indicates that multi-peril cat bonds explain the lion's share of the return time series, whereas single-peril U.S. hurricane bonds and particularly single-peril U.S. earthquake bonds are associated with weaker effects. This is in line with Braun (2016), who documents that the majority of historical primary market issuances were multi-peril cat bonds.[20]

[18] We further address the issue of a potential exposure towards other asset classes on the individual fund level below.

[19] On the individual fund level (see section 4.4), we observe many funds with *CAT-CAPM* betas equal to one, suggesting that their portfolio composition closely replicates the cat bond market portfolio.

[20] It should be noted that a combination of the *perils model* and the *spread model* does not improve the fit, since the factors of both are buried in CATMKT and thus simply provide a different breakdown of the same variance.

Table 7: Asset-class models

	(1)	(2)	(3)	(4)
MSCI	–0.01	0.01		
	(0.01)	(0.01)		
TREASURY	–0.01	0.00		0.03
	(0.05)	(0.03)		(0.04)
CORPORATE	0.00	0.04	0.03	0.01
	(0.04)	(0.04)	(0.03)	(0.04)
MUNICIPAL	0.04	0.06		0.05
	(0.03)	(0.04)		(0.03)
MORTGAGE	0.11		0.09	
	(0.10)		(0.07)	
CONVERTIBLE	0.04			0.03**
	(0.03)			(0.02)
REAL ESTATE	0.01	0.00	0.01	0.00
	(0.05)	(0.05)	(0.05)	(0.05)
HEDGE FUNDS	0.02		0.06*	
	(0.06)		(0.03)	
COMMODITY	0.00	0.00	–0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Constant (alpha)	0.30***	0.32***	0.30***	0.32***
	(0.08)	(0.08)	(0.08)	(0.08)
Adj. R^2	0.01	0.02	0.02	0.02
Obs.	168	168	168	168

This table shows the regression coefficients, intercepts (constant), and adjusted R-squareds of four different asset-class factor models run against our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are based on Newey and West (1987) with lags of four. The time series start in January 2002 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The residuals of the aforementioned regressions as shown in Figure 3 reveal an interesting fact. Overall, the models capture the time-series variation quite well. The only exception is the August 2005 return, which was heavily influenced by Hurricane Katrina. Neither the single-peril U.S. hurricane factor (USHU) nor the (rotated) cat bond market factors (CATMKT, CATMKO1, and CATMKO2) seem to capture this effect. Hence, we need to take a closer look at the underlying data. According to information from Aon Benfield, a total of 67 transactions were outstanding in August 2005. One of them, the indemnity-triggerd multi-peril bond KAMP Re covering U.S. hurricanes and earthquakes, was the first cat bond that ever defaulted due to a natural disaster (see Artemis Deal Directory). KAMP Re generated a return of –5% in August 2005. Due to its multi-peril status, however, this is not reflected by USHU. Similarly, the overall market index did not react, because the bond's portfolio weight amounted to no more than 13%. Nevertheless, we observe a clear reaction of our ILS fund index. This is due to the fact that the latter comprises merely 14 constituents in August 2005, five of which exhibit a negative return of at least 3.8%. Evidently, these funds must have exhibited a much higher exposure to KAMP Re than the

Table 8: Risk-factor models

	(1)	(2)	(3)	(4)
MKTRF	0.01		0.02*	0.01
	(0.01)		(0.01)	(0.01)
SMB	0.00		0.00	0.00
	(0.02)		(0.02)	(0.02)
HML	0.01		0.01	
	(0.02)		(0.02)	
TERM	0.03*	0.00		0.03*
	(0.02)	(0.02)		(0.02)
DEF	0.03**			0.03*
	(0.02)			(0.02)
HYIELD		0.04***		
		(0.01)		
MORTGAGE		0.12		
		(0.10)		
MOM			–0.01	
			(0.01)	
PTFSBD				0.00
				(0.00)
PTFSFX				0.00
				(0.00)
PTFSCOM				0.00
				(0.00)
Constant (alpha)	0.34***	0.31***	0.35***	0.34***
	(0.08)	(0.08)	(0.07)	(0.07)
Adj. R^2	0.01	0.03	0.00	0.00
Obs.	168	168	168	168

This table shows the regression coefficients, intercepts (constant), and adjusted R-squareds of four different risk-factor models run against our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are Newey and West (1987) with lags of four. The time series start in January 2002 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

market portfolio.[21] By controlling for this single extreme outlier through a dummy variable, we are able to increase the adjusted R-squared for the *CAT-CAPM* to 0.78 and for the other three models to 0.80 (see Columns (5) to (8) of Table 10).

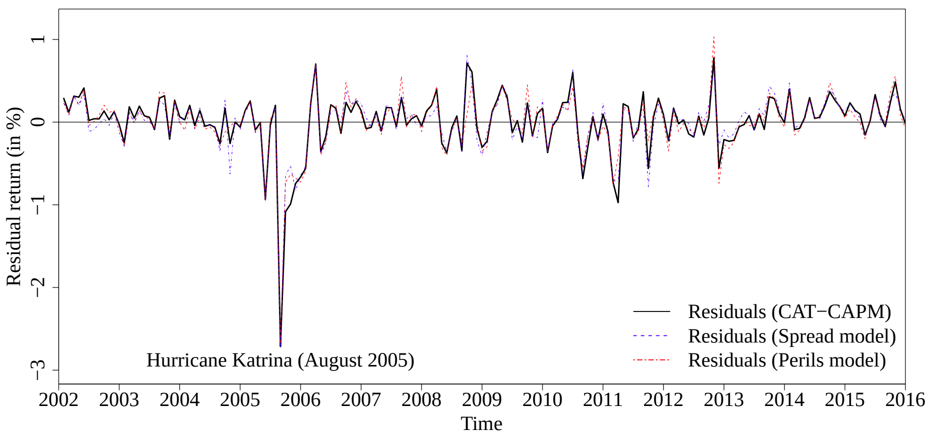
[21] According to Aon Benfield, KAMP Re suffered from an extreme negative return (-78%) in September 2005. Despite its low weight in the market portfolio, this effect is large enough to be captured by CATMKT, CATMKO1, and CATMKO2. Consequently, the corresponding residual in Figure 3 is much smaller.

Table 9: Control regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CATMKT	0.69***	0.70***	0.70***	0.70***	0.70***	0.71***	0.71***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
MKTRF		0.00					
		(0.01)					
TERM			0.00				
			(0.01)				
DEF				–0.01			
				(0.01)			
HYIELD					–0.01		
					(0.01)		
CONVERTIBLE						–0.01	
						(0.01)	
HEDGE FUNDS							–0.02
							(0.02)
Constant (alpha)	–0.02	–0.02	–0.02	–0.02	–0.02	–0.02	–0.02
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Adj. R^2	0.67	0.67	0.67	0.67	0.67	0.67	0.67
Obs.	168	168	168	168	168	168	168

This table shows the regression coefficients, intercepts (constants), and adjusted R-squareds of asset-class factors and risk factors from traditional models run against our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are based on Newey and West (1987) with lags of four. The time series start in January 2002 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 3: Residuals of the ILS-specific factor models



This figure illustrates the residuals of the regressions of our ILS fund index on the *CAT-CAPM*, the *spread model*, and the *perils model*. All variables are excess returns. The substantial downward spike occurs in August 2005. The time series start in January 2002 and end in December 2015.

Table 10: New ILS-specific factor models

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CATMKT	0.69***				0.68***			
	(0.09)				(0.09)			
CATMKO		0.26*				0.24		
		(0.15)				(0.16)		
BBCAT		0.59***				0.58***		
		(0.07)				(0.06)		
CATMKO1			0.28*				0.27	
			(0.15)				(0.16)	
TERM3Y			0.64***				0.66***	
			(0.07)				(0.08)	
DEFCORP			0.59***				0.58***	
			(0.07)				(0.06)	
DEFCAT			0.59***				0.58***	
			(0.07)				(0.06)	
CATMKO2				0.87***				0.85***
				(0.13)				(0.12)
USHU				0.33***				0.33***
				(0.03)				(0.03)
USEQ				0.07**				0.07**
				(0.03)				(0.03)
KATRINA					–2.74***	–2.74***	–2.76***	–2.70***
					(0.06)	(0.05)	(0.05)	(0.06)
Constant (alpha)	–0.02	0.05	0.04	0.02	0.01	0.07*	0.06	0.04
	(0.08)	(0.05)	(0.05)	(0.05)	(0.07)	(0.04)	(0.04)	(0.04)
Adj. R^2	0.67	0.69	0.69	0.69	0.78	0.80	0.80	0.80
Obs.	168	168	168	168	168	168	168	168

This table shows the regression coefficients, intercepts (constants), and adjusted R-squareds of the new ILS-specific factor models run against our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are based on Newey and West (1987) with lags of four. The time series start in January 2002 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

4.3 Robustness

Subperiods

To assess the robustness of our results, we separate the overall sample (January 2002 to December 2015) into four equally long subperiods and fit the *perils model* to the excess return time series of the aggregate ILS fund index. During the period from July 2005 to December 2008, we also include the Katrina dummy variable introduced above. Table 11 shows the respective results.[22] First, the *perils model* performs very well over the last three subperiods with adjusted R-squareds between 0.83 and 0.89. The orthogonalized cat bond market factor (CATMKO2) as well as the single-peril hurricane factor (USHU) are highly significant at all times, meaning that the majority of funds is constantly invested in multi-peril bonds and single-peril U.S. hurricane bonds. However, the single-peril earthquake factor (USEQ)

[22] Unreported results that underline the robustness of the other three ILS factor models are available upon request.

Table 11: Robustness with regard to subperiods

	(1) 01/2002–06/2005	(2) 07/2005–12/2008	(3) 01/2009–06/2012	(4) 07/2012–12/2015
CATMKO2	0.88***	0.97***	0.91***	0.24***
	(0.11)	(0.16)	(0.03)	(0.06)
USHU	0.41***	0.37***	0.27***	0.40***
	(0.06)	(0.08)	(0.05)	(0.03)
USEQ	0.10	0.05	0.25***	0.00
	(0.17)	(0.03)	(0.08)	(0.09)
KATRINA		–2.63***		
		(0.08)		
Constant (alpha)	0.00	–0.02	–0.06	0.18***
	(0.10)	(0.07)	(0.07)	(0.03)
Adj. R^2	0.50	0.83	0.89	0.83
Obs.	42	42	42	42

This table shows the regression coefficients, intercepts (constants), and adjusted R-squareds of the *perils model* over different time periods. The dependent variable is the excess return of the ILS fund index over the one-month T-Bill rate. The model is augmented by the Katrina dummy during the period July 2005 to December 2008. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

is only significant in the time period from January 2009 to June 2012. This could be due to the fact that many funds gain earthquake risk exposure through multiperil bonds. Second, we observe a much lower explanatory power for the subperiod from January 2002 to June 2005 (adjusted R-squared: 0.50). A likely reason is that only few ILS funds existed in those early days of the industry. Hence, portfolio compositions that differ from the market indices have a stronger impact. Third, we find a significant alpha of 0.18% per month in the most recent subperiod. Until the beginning of this time span, the ILS market itself and the variety of available instruments had already grown substantially. Consequently, the alleged abnormal return of the funds could in fact be generated by non-cat-bond portfolio constituents, which are not picked up by our model. This suspicion is confirmed by a structural break analysis on the entire sample. Using a supremum Wald test, we are able to identify a regime change in October 2011, which marks the beginning of the recent period of strong growth in collateralized reinsurance transactions (see AON Benfield, 2016).

Subindices

A further robustness check is conducted by regressing our ILS fund indices for the Bloomberg fund categories on the *perils model* with Katrina dummy. Table 12 shows the respective results. "Fixed Income" ILS funds seem to exhibit a significantly negative abnormal monthly return (alpha), implying that the constituents of this category have underperformed the benchmark during the time period under consideration. In contrast, insignificant alphas can be documented for the categories "Alternative" and "Other." The latter additionally exhibits a lower adjusted R-squared. This hints at the possibility that funds in this category might also invest in additional asset classes apart from ILS. To test this hypothesis,

Table 12: Robustness with regard to subindices

	(1)	(2)	(3)	(4)	(5)	(6)
		Fund category			Current status	
	All Funds	Alternative	Fixed Income	Other	Live	Dead
CATMKO2	0.85***	0.90***	0.73***	0.91***	0.91***	0.71***
	(0.12)	(0.11)	(0.17)	(0.32)	(0.15)	(0.07)
USHU	0.33***	0.31***	0.28***	0.39***	0.33***	0.29***
	(0.03)	(0.03)	(0.02)	(0.06)	(0.03)	(0.03)
USEQ	0.07**	0.19***	0.26***	–0.23***	0.02	0.21***
	(0.03)	(0.03)	(0.02)	(0.06)	(0.04)	(0.03)
KATRINA	–2.70***	–1.18***	–0.96***	–5.64***	–3.42***	–1.38***
	(0.06)	(0.05)	(0.07)	(0.15)	(0.07)	(0.04)
Constant (alpha)	0.04	0.03	–0.09**	0.17	0.08	–0.07**
	(0.04)	(0.04)	(0.05)	(0.11)	(0.05)	(0.04)
Adj. R^2	0.80	0.67	0.80	0.56	0.77	0.68
Obs.	168	162	168	168	168	136

This table shows the coefficients of the *perils model* augmented by the Katrina dummy. The dependent variable in column (1) is the return of the ILS fund index over the one-month T-Bill rate. The dependent variables in columns (2) to (4) are the excess returns of ILS fund categories. The dependent variables in columns (5) and (6) are excess returns for ILS funds distinguished by their current status (i.e, dead or live). The time period for the different excess return indices ranges between January 2002 and December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

one could run a style analysis on the individual funds, using the full asset-class factor model shown in Table 7. Another explanation could be holdings in non-cat-bond ILS such as extreme mortality bonds or collateralized reinsurance, which are not captured by our risk factors. Finally, the significantly negative alphas for defunct funds reported in the last column of Table 12 suggest underperformance to be the main reason for failure.

Out-of-sample analysis

Finally, we test the capability of our factor models to explain an alternative ILS fund portfolio. For this purpose, we substitute the dependent variable in our regressions by the commercially-published EurekaHedge ILS Advisers Index introduced in the first part of section four. The results, which are reported in Table 13, indicate that our models are well suited to describe the excess return time series of the EurekaHedge ILS Advisers Index with adjusted R-squareds of between 0.74 and 0.77. We may thus conclude that in-sample overfitting is unlikely to be an issue.

4.4 The cross section of expected excess returns

In this section, we draw on our new factor models to explain differences in the cross section of the expected excess returns of ILS funds. From now on, the dummy variable *KATRINA* will no longer be included in the models, since it merely captures a single outlier in the time series and is therefore irrelevant for the cross-sectional analysis. We follow Fung and Hsieh (2004) as well as Chen et al. (2010) and only include

Table 13: Out-of-sample robustness

	(1)	(2)	(3)	(4)
	Eurekahedge	Eurekahedge	Eurekahedge	Eurekahedge
CATMKT	0.62***			
	(0.11)			
CATMKO		0.30		
		(0.24)		
BBCAT		0.54***		
		(0.11)		
CATMKO1			0.32	
			(0.24)	
TERM3Y			0.62***	
			(0.12)	
DEFCORP			0.54***	
			(0.10)	
DEFCAT			0.55***	
			(0.11)	
CATMKO2				0.81***
				(0.18)
USHU				0.27***
				(0.03)
USEQ				0.18***
				(0.02)
Constant (alpha)	0.05	0.09	0.08	0.05
	(0.09)	(0.06)	(0.06)	(0.05)
Adj. R^2	0.74	0.75	0.75	0.77
Obs.	120	120	120	120

Results for the regressions of the return on the EurekaHedge ILS Advisers Index over the one-month T-Bill rate on the four ILS-specific factor models. Standard errors in parentheses are based on Newey and West (1987) with lags of four. The Eurekahedge ILS Advisers Index starts in January 2006 and ends in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

funds that have at least 24 months of consecutive return data. As a consequence, our sample reduces from 57 to 50 funds.[23] Each fund is considered based on its full return time series.

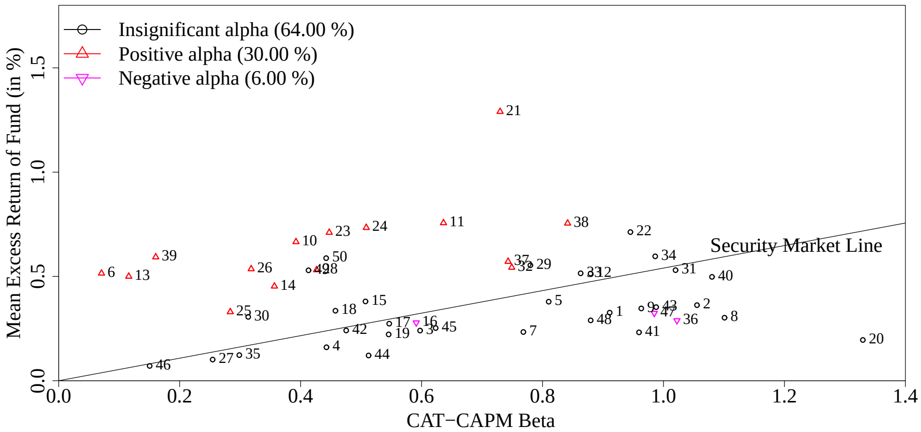
In Figure 4, we have plotted the actual mean excess returns of the ILS funds against their cat bond market betas from the *CAT-CAPM*. If ILS funds only invest in a diversified basket of cat bonds, their returns should increase with beta, i.e., there should be a linear relationship between systematic risk and return.[24] Most of the funds exhibit a beta between 0.10 and 1.00. For six of them, however, we find a *CAT-CAPM*-beta above 1.00. This might be due to leverage or the overweighing of riskier cat bond tranches relative to the market portfolio. Interestingly, though, the returns of these funds are no larger than those of their peers with lower betas. Moreover, all funds with significantly positive alphas (based

[23]We also ran the analysis with at least 36 months of consecutive return data. Although this criterion substantially reduces our sample to 38 funds, the key findings remain unchanged.

[24]The fact that not all funds in our sample operate(d) during the same time period can impair the linear relationship.

on the *CAT-CAPM*) have a beta exposure below 0.85. Again, this is an indication for a deviation from the cat bond market portfolio, potentially even due to assets from other ILS categories.

Figure 4: CAT-CAPM beta representation



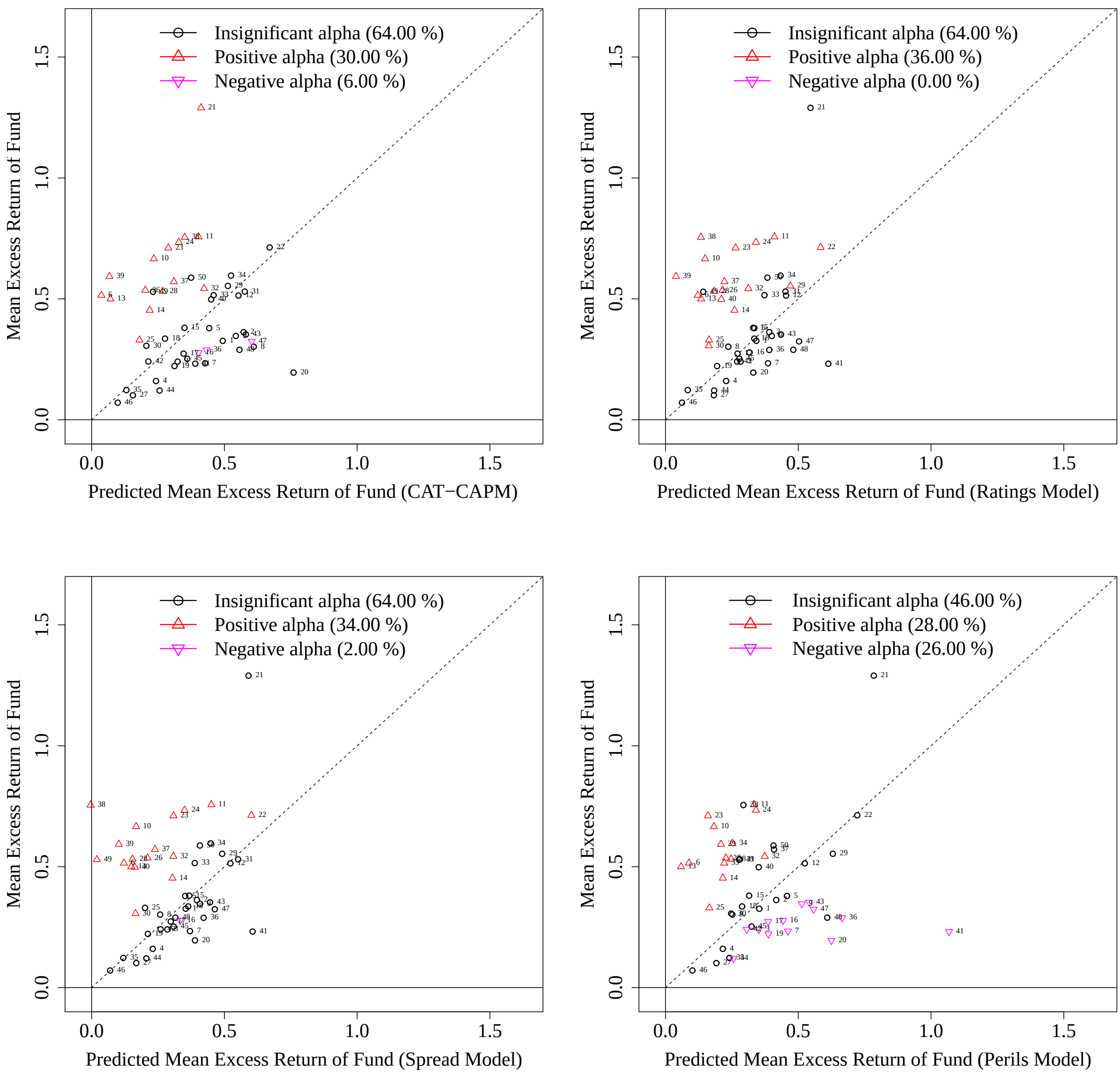
This figure illustrates the actual mean excess returns of 50 ILS funds against their beta estimated by the *CAT-CAPM*. Black circles indicate insignificant alpha values. Red upward-pointing triangles indicate significantly positive alphas at the 10% level. Magenta downward-pointing triangles indicate significantly negative alphas at the 10% level. The percentage of insignificant, significantly positive, and significantly negative alphas are documented in the legend. The security market line is drawn in excess of the risk-free rate, with the slope being the excess market return of catastrophe bonds. Note that each fund is considered based on its full return series. Hence, the time periods for which alphas are detected are not congruent.

Figure 5 illustrates the cross-sectional results by plotting the actual mean excess returns against the mean excess return predicted by the four ILS-specific factor models. Positive-significant, negative-significant, and insignificant alphas have been highlighted, and their percentages can be found in the legend. Funds without abnormal excess returns should be concentrated along the dotted 45-degree line, whereas notable deviations from this line should coincide with positive or negative alphas. However, for the *CAT-CAPM*, the *ratings model*, and the *spread model*, several funds that lie substantially below the 45-degree line exhibit insignificant alphas. Only the *perils model* seems to be sufficiently well suited to provide a clean separation of ILS funds with significantly positive and negative alphas.[25] Moreover, the *CAT-CAPM* cannot explain the positive abnormal returns of 30.00% of the ILS funds in the sample. At the same time, only 6.00% of all ILS funds underperformed it as a benchmark. Surprisingly, both the *ratings-based model* and the *spread model* leave slightly higher percentages of significantly positive alphas (36.00% and 34.00%) and a lower fraction of negative alphas (0.00% and 2.00%) than the *CAT-CAPM*. Despite their better fit to the time series found above, they thus seem to be a much less challenging

[25] More detailed cross-sectional information can be found in Table 18 in the Appendix, which, e.g., shows that dead funds as well as funds in the Bloomberg category "Fixed Income" exhibit the lowest percentages of positive alphas across all four ILS-specific factor models. This is another indication that managers, which ceased operations, were probably less successful than their peers. In addition, it hints at the possibility that ILS funds that classify themselves as "Fixed Income" tend to pursue a buy-and-hold rather than an active approach, thus disposing of less wiggle room to generate alpha returns.

benchmark for ILS funds. Finally, for the *perils model*, the number of funds with significantly negative alphas rises substantially to 26.00%, implying that many more managers were unable to earn back their fees. Another 46.00% of the funds exhibit an insignificant alpha. Hence, we can single out the *perils model* as the most challenging benchmark of the four. Nevertheless, it still leaves the positive abnormal returns of 28.00% of the ILS funds unexplained. Such a result is not uncommon for alternative investment funds. A similar percentage is, e.g., found by Edwards and Caglayan (2001) as well as Capocci and Hübner (2004), who study the performance of hedge funds. Studies in the mutual fund space, in contrast, usually report a much lower fraction of abnormal returns (see, e.g., Dahlquist et al., 2000). In any case, the positive alphas raise the question of whether approximately one quarter of all ILS funds were lucky, whether they are indeed able to outperform the market for cat bonds, or whether their alphas are in fact risk exposures to other (traditional or ILS) assets that are not captured by our factor models. We will address this question in the next section.

Figure 5: Predicting the cross-section of ILS funds



In this figure, we plotted the actual mean excess returns of 50 ILS funds against the mean excess returns predicted by the *CAT-CAPM* (upper left), the *ratings model* (upper right), the *spread model* (bottom left), and the *perils model* (bottom right). Black circles indicate insignificant alpha values. Red upward-pointing triangles indicate significantly positive alphas at the 10% level. Magenta downward-pointing triangles indicate significantly negative alphas at the 10% level. The legend on top of each graph highlights the percentage of insignificant, significantly positive, and significantly negative alphas predicted by the respective model. Note that each fund is considered based on its full return series. Hence, the time periods for which alphas are detected are not congruent.

4.5 Performance attribution

Exposure to ILWs

In this section, we further investigate whether the 28% of ILS funds that outperformed our *perils model* are in fact investing in other financial instruments. If some of the funds invest in traditional asset classes, we would measure an outperformance, since the *perils model* does not control for such exposures. However, unreported results indicate no significant regression coefficients with regard to the asset-class factors presented in Table 2. In addition, none of the alphas turns insignificant. Another reason for the positive abnormal returns might be positions in non-cat-bond ILS that are not captured by the *perils model*. Indices for such instruments are generally unavailable, the only exception being ILWs. For the latter, we can draw on the excess returns of the Mercury Investable Catastrophe Risk Index, also known as MiCRIX, which tracks the performance of a diversified portfolio of peak-peril ILWs and starts in January 2006.[26] Due to their structural differences compared to cat bonds, ILWs can be expected to exhibit a somewhat different return behavior, despite transferring the same types of catastrophe risk. We integrate the variable $MiCRIX_t$ into the *perils model* and define the resulting extended *perils model* as:

$$R^e_{i,t} = \alpha + \beta_{i,1} CATMKO2_t + \beta_{i,2} USHU_t + \beta_{i,3} USEQ_t + \beta_{i,4} MiCRIX_t. \tag{5}$$

As shown in Table 14, the positive alphas for four out of the 14 funds identified in the previous section become insignificant. Consequently, beta exposures to ILWs are one source of the abnormal returns that were left unexplained by the *perils model*.

Table 14: Explaining alpha with ILW exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.52***	0.47***	0.43***	0.22***	0.60***	0.51***	0.39***
	(0.06)	(0.13)	(0.07)	(0.05)	(0.17)	(0.08)	(0.05)
Adj. R^2	0.35	0.36	0.02	0.42	–0.03	0.56	0.64
# of obs.	118	115	92	91	78	55	55

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Alpha	0.16***	0.31***	0.28***	–0.05	0.08	0.12	0.25
	(0.06)	(0.04)	(0.06)	(0.10)	(0.09)	(0.08)	(0.18)
Adj. R^2	0.21	0.63	0.65	0.79	0.74	0.82	0.11
# of obs.	54	52	48	36	34	34	24

This table shows the intercept (i.e., alpha) and adjusted R-squareds from the extended *perils model* fitted to the return time series of 14 ILS funds. The latter were identified based on positive abnormal returns under the *perils model* in Table 18. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. All funds are considered based on the congruent time period from January 2006 to December 2015.

[26] In contrast to cat bonds, ILWs are uncollateralized and unfunded double-trigger contracts, whose main trigger relies on an insurance industry loss index. For a detailed discussion of ILWs and catastrophe swaps, refer to Braun (2011).

Fund characteristics

Next, we test whether the performance differences are associated with certain fund characteristics. To this end, we draw on the natural logarithm of current AuM, the natural logarithm of fund age (active years), performance fees, and load fees. We do not include the expense ratios, top ten holdings, and cash reserves, as these figures are available for no more than 25 funds.[27] We run a series of cross-sectional regressions of the fund alphas (based on the *perils model*) on these independent variables. Table 15 shows the respective results. The sample size in each column is determined by the number of funds for which we have access to the necessary data.

Table 15: Explaining alpha with fund characteristics

	(1)	(2)	(3)	(4)	(5)
ln(AuM)	0.87***				0.89***
	(0.29)				(0.27)
ln(Age)		–0.51			–1.47*
		(0.63)			(0.77)
Performance fee			0.18***		0.19***
			(0.06)		(0.05)
Load fees				–0.80***	–0.33
				(0.28)	(0.28)
Constant	–4.00**	1.51	–0.70	1.55**	–2.55
	(1.57)	(1.15)	(0.71)	(0.69)	(1.69)
Obs.	48	50	44	38	38
Adj. R^2	0.13	–0.01	0.17	0.13	0.37

This table shows the coefficients, constants, heteroskedasticity-consistent standard errors (in parentheses), and adjusted R-squareds for the cross-sectional regressions of each fund's alpha on the natural logarithm of assets under management, ln(AuM), the natural logarithm of fund age measured in years, ln(Age), the performance fee (in % p.a.), and the (sum of front and back) load fees (in % p.a.). The sample size for each analysis varies based on data availability. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

As opposed to Chen et al. (2004), who demonstrate that size erodes the performance of mutual funds, we find a significant and positive relationship between AuM and abnormal returns. This also contradicts evidence from the hedge fund industry (see, e.g., Ammann and Moerth, 2005).[28] Figure 6, in which we have plotted the alphas against fund size, reveals another important aspect. Funds exceeding USD 680 million in AuM are not outperformers on average. Consequently, there might be an optimal size for ILS funds.[29] This finding, however, raises questions about the direction of causality. In other words, does fund size cause performance or vice versa? In the first case, larger funds could beat the benchmark due to economies of scale and the fact that they tend to command more resources. This may enable them to make better investment decisions or simply to access other types of ILS, which are more complex to handle than cat bonds. When growing too large, however, they might suffer from diseconomies of

[27]Unreported results for the 25 funds showed no significant impact of these three variables.

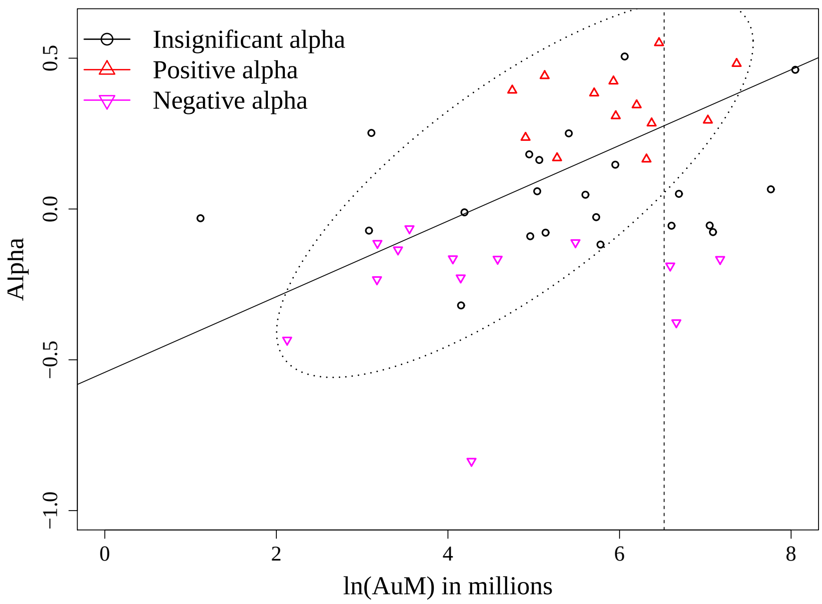
[28]We have to carefully interpret this finding, given it is based on a single cross section at the end of the sample period.

[29]Note that we have tested this notion by means of a nonlinear regression term and obtained insignificant results, which we attribute to the fact that there are very few funds in the sample with AuM above USD 680 mn.

scale because they have to invest a lot of capital in a relatively small market, where highly profitable investment opportunities are sometimes rare. In the second case, large funds could be large because their outperformance increases their size and attracts investor capital. Similarly, small funds could be small because their underperformance decreases their size and repels investor capital.

In addition to the effect of fund size, we document a slightly significant negative relationship between fund age and alpha returns. This is in line with the recent results of Pástor et al. (2015) for a large mutual fund sample. Again, two explanations are conceivable: either younger funds are more skilled than older funds because they employ the latest strategies and technologies, or they simply benefit from the fact that, in the few years of their existence, they were able to select from a much broader menu of ILS instruments. The time series of older funds, on the contrary, date back to the early days of the ILS market, when most of the activity focused almost exclusively on cat bonds. Consequently, a larger part of their historical returns can be well explained by the *perils model*.

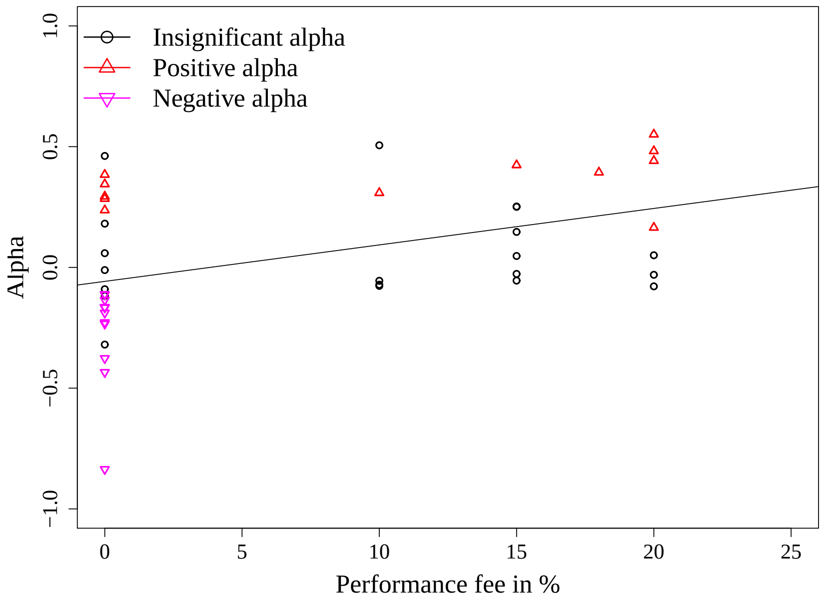
Figure 6: Alpha and fund size



This figure illustrates the abnormal returns (alpha) from the *perils model* of 48 ILS funds against their respective fund size (two funds do not have AuM information). Fund size on the x-axis is the natural logarithm of assets under management (AuM) in USD millions. Black circles indicate insignificant alpha values. The solid black line shows the estimated slope of alpha against fund size based on funds not exceeding USD 680 mn in AuM. The vertical black line (dashed) indicates a break in the functional relationship between alpha and fund size at USD 680 mn. Red upward-pointing triangles indicate significantly positive alphas at the 10% level. Magenta downward-pointing triangles indicate significantly negative alphas at the 10% level.

Finally, the regression coefficient of the performance fee is positive. This is consistent with what we know from the hedge fund space (see, e.g., Edwards and Caglayan, 2001). According to the last column of Table 15, a 100-basis-point increase in the performance fee implies an additional abnormal return of 19 basis points. Figure 7 is a graphical illustration of the positive relationship between incentive fees and alpha. The most striking observation is that all funds with a significantly negative alpha exhibit no performance fee. We also notice that four of the funds with a significantly positive alpha can be found in the highest fee bracket of 20%. One of these four is the fund with the largest significant alpha in the entire sample. In contrast, the worst performing ILS fund in the sample has a performance fee of zero. These results indicate an effective incentivization of skilled managers.

Figure 7: Alpha and performance fee



This figure illustrates the abnormal returns (alpha) from the *perils model* of 44 ILS funds against their respective performance fee (six funds do not have information about performance fees). Performance fee on the x-axis is provided in percentages. Black circles indicate insignificant alpha values. The solid black line shows the estimated slope of alpha against performance fees. Red upward-pointing triangles indicate significantly positive alphas at the 10% level. Magenta downward-pointing triangles indicate significantly negative alphas at the 10% level.

Market timing

So far, some of the returns left unexplained by the *perils model* could be attributed to ILW exposures of the respective ILS funds. In addition, while not proof per se, our results for fund size, fund age, and performance fee could at least be seen as weak evidence for talented managers. Owing to these insights, we deem it necessary to run further analyses with the aim of distinguishing skill from luck. As outlined by Kacperczyk et al. (2014), fund manager skill is either the ability to pick the right securities or to time the market. It is virtually impossible for us to control for the first aspect, since we do not have any information about the funds' portfolio constituents. The second one, however, can be addressed using the approach of Treynor and Mazuy (1966). A manager with timing abilities would increase his exposure towards cat bonds before the market generates positive returns and decrease his exposure in case of an upcoming downturn. In this case, we may thus expect a convex relationship between the cat bond market and the fund returns. The latter can be accounted for by adding a squared cat bond market factor, CATMKT^2, to the *CAT-CAPM*:

$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKT_t + \gamma_{i,1} CATMKT^2_t + \epsilon_{i,t}. \tag{6}$$

In the same spirit, we extend the *perils model* by squared factors in order to pick up timing abilities for multi-peril bonds, single-peril U.S. hurricane bonds, and single-peril U.S. earthquake cat bonds:

$$R^e_{i,t} = \alpha_i + \beta_{i,1} CATMKO2_t + \beta_{i,2} USHU_t + \beta_{i,3} USEQ_t + \gamma_{i,1} z^2_t + \epsilon_{i,t}, \tag{7}$$

where z_t is either CATMKO2, USHU, or USEQ. In both models, the convex relationships, and hence successful market timing, would be reflected by positive regression coefficients for the squared factors.

Table 16: Market timing

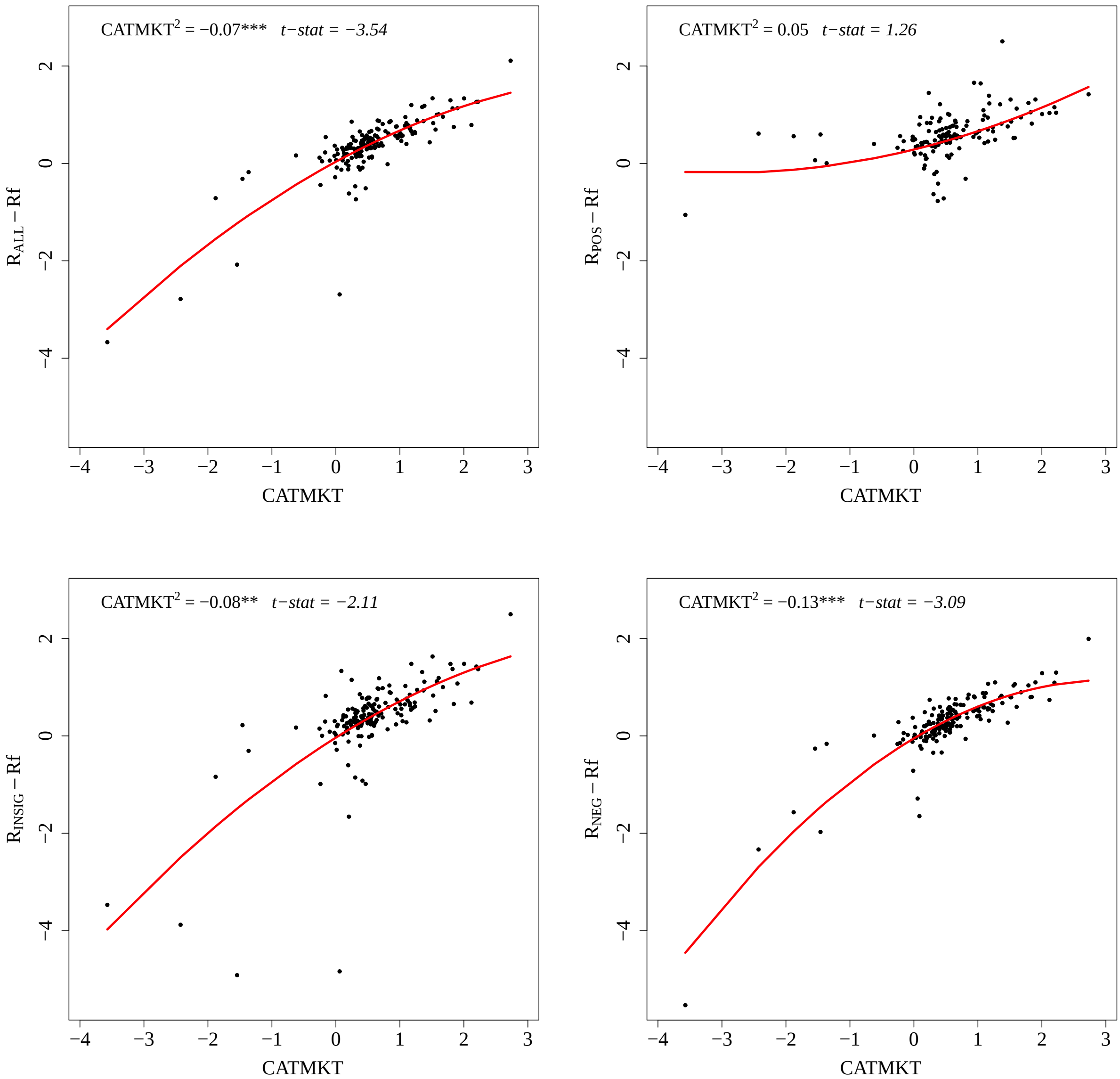
	(1)	(2)	(3)	(4)	(5)
CATMKT	0.71***				
	(0.07)				
CATMKT^2	-0.07***				
	(0.02)				
CATMKO2		0.66***	0.88***	0.88***	0.64***
		(0.16)	(0.13)	(0.13)	(0.16)
USHU		0.33***	0.27***	0.33***	0.26***
		(0.03)	(0.04)	(0.03)	(0.03)
USEQ		0.05	0.11***	0.12*	0.14**
		(0.03)	(0.03)	(0.07)	(0.06)
CATMKO2^2		-0.14***			-0.14***
		(0.04)			(0.04)
USHU^2			0.03**		0.03**
			(0.01)		(0.01)
USEQ^2				0.01	0.01
				(0.01)	(0.01)
Constant	0.03	0.09	0.01	-0.00	0.06
	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
Obs.	168	168	168	168	168
R^2	0.69	0.71	0.70	0.69	0.72

This table shows the coefficients of the *CAT-CAPM* augmented by the squared catastrophe bond market factor in Column (1). Columns (2) to (4) show the *perils model* sequentially augmented by its squared factors. Column (5) augments the *perils model* by all of its squared components. Standard errors in parentheses are based on Newey and West (1987) with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 16 contains the results for five time-series regressions of the ILS fund index excess returns on the *CAT-CAPM* and the *perils model* with market timing factors. The coefficient of the squared cat bond market factor (CATMKT^2) in Column (1) is significantly negative, implying a concave relationship. This suggests that ILS funds rebalance their portfolios at unfavorable points in time, therefore producing stronger downturns and weaker upturns compared to the overall cat bond market. Furthermore, they seem to fail at timing multi-peril cat bonds, as we observe a significant and negative impact of the squared rotated market factor (CATMKO2^2) in Columns (2) and (5). In contrast, USHU^2 exhibits a significantly positive coefficient. Hence, ILS funds appear to be successful in timing single-peril U.S. hurricane bonds. Two crucial strategies in this regard could be live and dead cat trading. In the first case, cat bonds are bought or sold while a storm is active (e.g., before landfall). An ILS fund can thus speculate on the strength and trajectory of the latter. In the second case, the storm has already dissipated but the final estimate of insurance losses is still outstanding. Consequently, one may trade based on an opinion as to which cat bonds will be ultimately triggered. Both strategies allow adept managers to benefit from price movements in the secondary market.

In a further step, we split the sample into positive (14 funds), insignificant (23 funds), and negative-alpha funds (13 funds) based on the *perils model*. We then run the *CAT-CAPM* market timing regression on a equally-weighted index for each group. Figure 8 shows the respective results. The graph in the upper left is based on the index for the complete sample and therefore graphically illustrates the effect that we have already seen in Column (1) of Table 16. The other three graphs help us to trace back the inability to time the market to the three subsamples. For the positive alpha funds shown in the upper right graph, we indeed observe a slightly convex relationship. However, since the coefficient is not statistically significant (0.05 with a t-statistic of 1.26), we cannot safely infer that market timing skills are present. In contrast, we find significant coefficients of –0.08 and –0.13 for the other two subsamples. Therefore, the weaker performance of ILS funds with insignificant and significantly negative alphas is, at least to some extent, driven by poor market timing decisions.

Figure 8: Market timing of ILS funds with different abnormal performance



In this figure, we plotted the excess returns of ILS fund indices against the corresponding excess returns on the cat bond market (CATMKT). The dependent variable in the upper left graph is the aggregated excess return of all ILS funds. The dependent variable in the upper right graph is the aggregated excess return of 14 ILS funds with positive alpha based on the *perils model*. The bottom left and bottom right graphs show the excess returns of aggregated insignificant and aggregated negative ILS funds based on the *perils model*. The red line in each graph indicates the fitted regression line according to Equation (6). The legend on top of each graph highlights the coefficient value of $CATMKT_t^2$ and the corresponding t-statistic based on HAC standard errors of Newey and West (1987) with lags of four. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Measuring luck in the estimated alphas

Since market timing is not the driving force of abnormal ILS fund performance, we finally want to know to which extent our results are simply attributable to luck. For that purpose we apply the methodology of False Discovery Rates (FDR) by Barras et al. (2010), which allows us to identify funds that truly outperform (and truly underperform). In other words, we want to ensure that our positive-alpha funds are not false discoveries in the sense that their measured alpha is positive and significant while the true alpha is zero. Vice versa, we also check whether negative alpha funds are truly unskilled or simply unlucky. Our initial significance level to identify positive and negative alpha funds is 10%. The significance levels by which we control for true positive-alpha and negative-alpha funds are 10%, 5%, and 1%. For details on the estimation procedure see Barras et al. (2010).

Table 17: Luck and alpha

	Left tail (i.e., negative alpha)		Right tail (i.e., positive alpha)	
	Unlucky funds $\hat{F}_{\gamma}^{-}$	Unskilled funds $\hat{T}_{\gamma}^{-}$	Skilled funds $\hat{T}_{\gamma}^{+}$	Lucky funds $\hat{F}_{\gamma}^{+}$
Significance level in % (γ)				
10	2.3%	23.7%	25.7%	2.3%
5	2.9%	13.1%	23.1%	2.9%
1	3.6%	2.4%	18.4%	3.6%

This table shows the impact of luck on the alpha distribution of individual ILS funds based on the *perils model*. The table counts the proportions of significant funds in the left and right tail of the cross-sectional t-statistic distribution at the three significance levels (γ) 10%, 5%, and 1%. To be included in the analysis, a fund must have at least 24 months of consecutive return data. The initial significance level for a fund to be considered outperforming or underperforming is at the 10% level.

The results are presented in Table 17. When we decrease the likelihood that lucky funds are classified as positive-alpha funds from 10% to 1%, we only observe a slight decrease in the proportion of skilled funds from 25.7% to 18.4%. This suggests that the majority of positive-alpha funds are truly skilled in what they do. Yet, when we decrease the likelihood that unlucky funds are classified as negative-alpha funds from 10% to 1%, we observe a strong decrease in the proportion of unskilled funds from 23.7% to 2.4%. This suggests that negative-alpha funds are mostly unlucky in what they do. These results are in contrast to Barras et al. (2010), who find more unskilled than skilled mutual funds.

Overall, our performance attribution helps to substantially narrow down the sources of abnormal returns in ILS funds. The fact that we can rule out both market timing abilities and luck for the positive-alpha funds leaves two plausible explanations for their outperformance. The most likely one are holdings of non-cat-bond ILS instruments such as collateralized reinsurance, whose return variation can, for the lack of an adequate benchmark index, not be captured by our *perils model*. This could be specifically confirmed for the case of ILWs. Furthermore, there remains a possibility that some ILS fund managers have the talent to pick the right securities. This view is supported by the fact that we found significant relationships between performance and certain fund characteristics (size, age, and performance fees).

Finally, for the negative-alpha funds, we may conclude that most of their managers have simply been unlucky, particularly with regard to their market-timing decisions.

5 Conclusion

The paper at hand adds to both the asset pricing and the ILS literature. It does so by focusing on three major contributions. First, we compiled an extensive sample of dedicated ILS funds, based on which we describe the typical characteristics and historical performance of these alternative investment vehicles. Second, we explore to which extent traditional factor pricing models are able to capture the return properties of diversified ILS portfolios, introduce four ILS-specific approaches, and test their explanatory power in a number of time-series and cross-sectional analyses. Third, we employ the new factor models to shed light on the question of whether a particular subset of ILS funds was able to generate positive abnormal returns in the past and aim to identify their determinants.

Our main findings can be summarized as follows. Judging by a whole battery of financial performance measures, ILS funds have exhibited a superior historical performance relative to corporate bonds and hedge funds, with which they are often compared. Furthermore, the factor models of Sharpe (1992), Fama and French (1993), Blake et al. (1993), Carhart (1997), and Fung and Hsieh (2004) are all completely unsuited to explain the returns in this market. Therefore, it can be concluded that ILS are indeed a zero-beta asset class in the classical sense. This, however, does by no means imply that there are no common factors to be found in ILS portfolios. Quite on the contrary, we are able to reveal several sources of systematic risk, which constitute what could be called exotic beta exposure. Without a doubt, the latter should be taken into account when aiming to assess the performance of investment managers that concentrate on this asset class. Our empirical results allow us to identify one specific factor model (the *perils model*) as the most challenging benchmark. Based on this model, we find positive alphas for about one quarter of all ILS funds. It is possible to attribute some of these abnormal returns to beta exposures associated with non-cat-bond ILS. Moreover, they are related to fund size, fund age, and performance fees. Finally, we do not find evidence for market timing abilities but can rule out pure luck by controlling for false discoveries.

A few limitations of our work constitute the basis for future research. Although the market has already been tested by Hurricane Katrina and the Tohoku Earthquake, a historical analysis does not convey a complete picture of the performance of ILS in general and cat bonds in particular. This is due to the fact that the recurrence periods of the extreme events that are securitized in this asset class can be as long as 1000 years. Against such a horizon, the 15 years of available time series data are no more than a blink of an eye. It therefore remains largely unclear, what level of expected excess returns investors can expect in the future. Answering this question and identifying long-run persistence in manager skill would require decades, if not centuries, of returns. Hence, a meaningful comparison of the risk premium offered by ILS relative to other asset classes needs to rely on simulation-based event data from a commercial catastrophe risk model. However, our perils model can be a useful tool in differentiating which funds will do better or worse if such extreme events occur. In addition, future research could aim at extending our perils model by further cat-bond risk factors. Currently, it can only explicitly distinguish single-peril U.S. wind and earthquake exposure, while leaving all other sources of systematic variation buried in the market factor. Consequently, it is not an optimal means for style analysis yet. Similarly, the new factor model could be complemented with factors that capture the returns of non-cat-bond ILS, such as collateralized reinsurance and life insurance securitizations, once those become available in a reliable form. Finally, more research is needed to understand whether the significant alpha returns identified in our sample can indeed be traced back to manager skill, which would require the actual portfolio holdings including buy and sell timing.

Appendix

Table 18: Time series regressions of individual funds on ILS-specific factor models

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
CAT-CAPM	Index	Fund category			Status	
Alpha distr.	All Funds	Alternative	Fixed Income	Other	Live	Dead
+	30.00%	35.29%	7.69%	40.00%	37.50%	0.00%
0	64.00%	58.82%	76.92%	60.00%	56.50%	90.00%
−	6.00%	5.88%	15.38%	0.00%	5.00%	10.00%
No. of funds	50	17	13	20	40	10

Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Ratings model	Index	Fund category			Status	
Alpha distr.	All Funds	Alternative	Fixed Income	Other	Live	Dead
+	36.00%	29.41%	15.38%	55.00%	45.00%	0.00%
0	64.00%	70.59%	84.62%	45.00%	55.00%	100.00%
−	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
No. of funds	50	17	13	20	40	10

Panel C	(1)	(2)	(3)	(4)	(5)	(6)
Spread model	Index	Fund category			Status	
Alpha distr.	All Funds	Alternative	Fixed Income	Other	Live	Dead
+	34.00%	29.41%	7.69%	55.00%	40.00%	10.00%
0	64.00%	70.59%	84.62%	45.00%	57.50%	90.00%
−	2.00%	0.00%	7.69%	0.00%	2.50%	0.00%
No. of funds	50	17	13	20	40	10

Panel D	(1)	(2)	(3)	(4)	(5)	(6)
Perils model	Index	Fund category			Status	
Alpha distr.	All Funds	Alternative	Fixed Income	Other	Live	Dead
+	28.00%	29.41%	7.69%	25.00%	35.00%	0.00%
0	46.00%	41.18%	30.77%	75.00%	45.00%	50.00%
−	26.00%	29.41%	61.54%	0.00%	20.00%	50.00%
No. of funds	50	17	13	20	40	10

This table shows the alpha distribution of individual ILS funds resulting from the ILS-specific factor models. To be included in the analysis, a fund must have at least 24 months of consecutive return data. Alphas reported as positive (+) or negative (−) are significant at least on the 10% level. The number of funds in each category is reported in the last row of the table.

References

Agarwal, V., Daniel, N. D., and Naik, N. Y. (2011). Do Hedge Funds Manage Their Reported Returns? *Review of Financial Studies*, 24(10):3281–3320.

AM Best (2015). Global Reinsurance: Segment Review. *Special Report*.

Ammann, M., Kind, A., and Seiz, R. (2010). What Drives the Performance of Convertible-Bond Funds? *Journal of Banking and Finance*, 34(11):2600–2613.

Ammann, M. and Moerth, P. (2005). Impact of Fund Size on Hedge Fund Performance. *Journal of Asset Management*, 6(3):219–238.

AON Benfield (2013). Reinsurance Market Outlook - Post Convergence - The Next USD100 Billion.

AON Benfield (2016). Insurance-Linked Securities: Alternative Markets Find Growth Through Competition.

Bantwal, V. J. and Kunreuther, H. C. (2000). A Cat Bond Premium Puzzle? *Journal of Psychology and Financial Markets*, 1(1):76–91.

Bao, J., Pan, J. U. N., and Wang, J. (2016). The Illiquidity of Corporate Bonds. *Journal of Finance*, 66(3):911–946.

Barras, L., Scaillet, O., and Wermers, R. (2010). False Discoveries in Mutual Fund Performance: Measuring the Role of Lucky Alphas. *Journal of Finance*, 65(1):179–215.

Blake, C., Elton, E. J., and Gruber, M. J. (1993). The Performance of Bond Mutual Funds. *Journal of Business*, 66(3):371–403.

Braun, A. (2011). Pricing Catastrophe Swaps: A Contingent Claims Approach. *Insurance: Mathematics and Economics*, 49(3):520–536.

Braun, A. (2016). Pricing in the Primary Market for Cat Bonds: New Empirical Evidence. *Journal of Risk and Insurance*, (forthcoming).

Braun, A., Müller, K., and Schmeiser, H. (2013). What Drives Insurers Demand for Cat Bond Investments? Evidence from a Pan-European Survey. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 38(3):580–611.

Capocci, D. and Hübner, G. (2004). Analysis of Hedge Fund Performance. *Journal of Empirical Finance*, 11(1):55–89.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57–82.

Carhart, M. M., Carpenter, J. N., Lynch, A. W., and Musto, D. K. (2002). Mutual Fund Survivorship. *The Review of Financial Studies*, 15(5):1439–1463.

Chen, J., Hong, H., Huang, M., Kubik, J. D., American, T., Review, E., and Dec, N. (2004). Does Fund Size Erode Mutual Fund Performance? The Role of Liquidity and Organization. *American Economic Review*, 94(5):1276–1302.

Chen, Y., Ferson, W., and Peters, H. (2010). Measuring the Timing Ability and Performance of Bond Mutual Funds. *Journal of Financial Economics*, 98(1):72–89.

Cumming, D., Fleming, G., and Schwienbacher, A. (2009). Style Drift in Private Equity. *Journal of Business Finance & Accounting*, 36(5-6):645–678.

Dahlquist, M., Engstrom, S., and Soderlind, P. (2000). Performance and Characteristics of Swedish Mutual Funds. *The Journal of Financial and Quantitative Analysis*, 35(3):409.

Edwards, F. R. and Caglayan, M. O. (2001). Hedge Fund Performance and Manager Skill. *Journal of Futures Markets*, 21(11):1003–1028.

Fama, E. F. and French, K. R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1):3–56.

Fang, J., Kempf, A., and Trapp, M. (2014). Fund Manager Allocation. *Journal of Financial Economics*, 111(3):661–674.

Fung, W. and Hsieh, D. A. (1997). Empirical Characteristics of Dynamic Trading Strategies: The Case of Hedge Funds. *Review of Financial Studies*, 10(2):275–302.

Fung, W. and Hsieh, D. A. (2000). Performance Characteristics of Hedge Funds and Commodity Funds. *Journal of Financial and Quantitative Analysis*, 35(3):291–307.

Fung, W. and Hsieh, D. A. (2004). Hedge Fund Benchmarks: A Risk-Based Approach. *Financial Analysts Journal*, 60(5):65–80.

Galeotti, M., Gürtler, M., and Winkelvos, C. (2013). Accuracy of Premium Calculation Models for CAT Bonds - An Empirical Analysis. *Journal of Risk and Insurance*, 80(2):401–421.

Getmansky, M., Lo, A. W., and Makarov, I. (2004). An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns. *Journal of Financial Economics*, 74(3):529–609.

Gürtler, M., Hibbeln, M., and Winkelvos, C. (2016). The Impact of the Financial Crisis and Natural Catastrophes on CAT Bonds. *Journal of Risk and Insurance*, (forthcoming).

Hagendorff, B., Hagendorff, J., and Keasey, K. (2013). The Shareholder Wealth Effects of Insurance Securitization: Preliminary Evidence from the Catastrophe Bond Market. *Journal of Financial Services Research*, 44(3):281–301.

Hagendorff, B., Hagendorff, J., Keasey, K., and Gonzalez, A. (2014). The Risk Implications of Insurance Securitization: The Case of Catastrophe Bonds. *Journal of Corporate Finance*, 25(2):387–402.

Kacperczyk, M., Nieuwerburgh, S. V., and Veldkamp, L. (2014). Time-Varying Fund Manager Skill. *Journal of Finance*, 69(4):1455–1484.

Newey, W. and West, K. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica: Journal of the Econometric Society*, 55(3):703–708.

Partner Re (2015). The Drivers of Catastrophe Bond Pricing. *Partner Reviews*.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2015). Scale and Skill in Active Management. *Journal of Financial Economics*, 116(1):23–45.

RMS (2012). Cat Bonds Demystified: RMS Guide to the Asset Class.

Sadka, R. (2010). Liquidity Risk and the Cross-Section of Hedge-Fund Returns. *Journal of Financial Economics*, 98(1):54–71.

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*, 19(3):425–442.

Sharpe, W. F. (1992). Asset Allocation: Management Style and Performance Measurement. *The Journal of Portfolio Management*, 18(2):7–19.

Smolka, A. (2006). Natural Disasters and the Challenge of Extreme Events: Risk Management from an Insurance Perspective. *Philosophical Transactions of the Royal Society A*, 364(1845):2147–2165.

Swiss Re (2006). Securitization: New Opportunities for Insurers and Investors. *Sigma 7/2006, Zurich.*

Swiss Re (2010). The Essential Guide to Reinsurance. *Report.*

Swiss Re (2013). Insurance-Linked Securities. *Market Update.*

Swiss Re (2016). Insurance-Linked Securities. *Market Update.*

Treynor, J. and Mazuy, K. (1966). Can Mutual Funds Outguess the Market? *Harvard Business Review*, 44(4):131–136.