Asset Pricing and Extreme Event Risk: Common Factors in ILS Funds

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Abstract

The returns of collective investment vehicles that focus on catastrophe (cat) bonds and other insurance-linked securities (ILS) behave unlike those of any other asset class. Therefore, traditional asset pricing models, such as the five-factor approach of Fama and French (1993) and the seven-factor approach of Fung and Hsieh (2004), are not suitable for these funds. We set up a comprehensive database, run an empirical performance analysis, and introduce four new factor models based on publicly-available indices, which explain the time-series and cross-sectional return characteristics of ILS funds. Our results indicate that the latter have historically exhibited a superior risk-adjusted performance. Despite a strong overall fit of the factor models, we are left with significant positive alphas for about one quarter of the funds in our sample. These abnormal returns exhibit a significant relationship with fund size and performance fees. However, it is challenging to attribute them to manager skill, luck, or beta exposures associated with non-cat-bond ILS.

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

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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 which 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 has witnessed substantial growth rates in the recent past (see, e.g., AON Benfield, 2015). 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). Such instruments may thus be considered a genuine alternative asset class. However, direct investments in cat bonds and other ILS require a lot of specific expertise (see, e.g., Braun et al., 2013). An alternative way to gain exposure is given by 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]

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 cat bonds 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 idea of an asset-class factor model as coined by 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 Sharpe's setup 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.

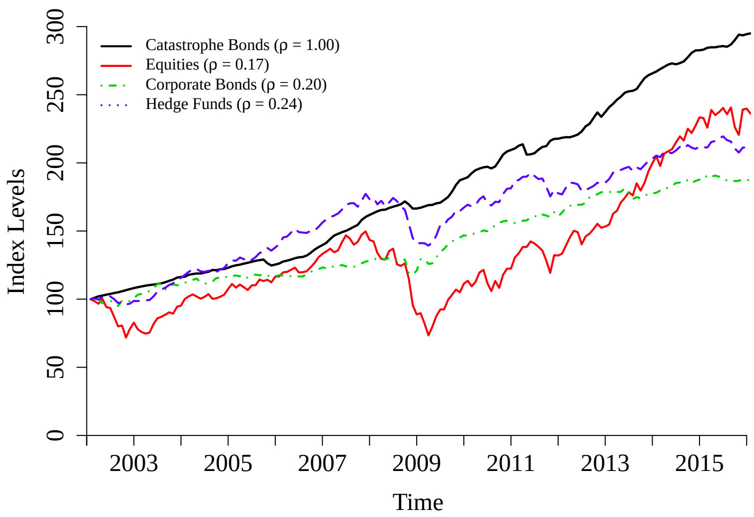
Regardless of the impressive historical performance and substantial diversification potential offered by ILS funds (see Figure 1), little is known about their return drivers to date. The paper at hand aims at filling this gap. Our contribution is threefold. First, we analyze the asset class' risk-return profile for the

[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 breed 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.

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 funds were able to outperform their peers on a risk-adjusted basis in the past.

Figure 1: Catastrophe bonds and other asset classes



This figure illustrates the development of cat 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 of the cat bond index over the considered time period amounted to 8.15%.

Our findings indicate that ILS funds exhibited a superior historical performance based on the Sharpe Ratio, the Sortino Ratio, the Excess Return on VaR, and the Calmar Ratio. 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 are able to 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 significant positive alphas for about one quarter of all funds. Although these are related to fund size and performance fees, it is currently challenging to ascertain whether they are attributable to manager skill, luck, or exotic beta exposures originating from non-cat-bond ILS.

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 Section 4.3, we test the robustness of our results for various subperiods and alternative ILS portfolios. 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, as well as in the Morningstar CISDM database. For each fund, we retrieved monthly net-of-fee total return data from Bloomberg. Apart from that, 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 who do not publish returns at all, it was possible to obtain data under confidentiality agreements 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 total number of funds identified amounts to 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 those funds without any classification have been subsumed under "Other".[5] Although this is a very broad categorization, it allows for a certain 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), what funds say they do is not necessarily what they actually do. 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

[3] It should be noted that Fermat Capital, which around USD 5 bn of AuM and is thus one of the largest dedicated ILS funds, 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 investors of hedge funds and private equity funds.

funds ("Live") and acquired or dissolved funds ("Dead"). Based on the latest AuM of 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 to be a reason for failure. However, only the difference in the maximum load fees is 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

When working with mutual and hedge fund return data, one needs to be aware of potential biases, which we need to scrutinize for ILS funds as well. These include survivorship bias, backfilling bias, self-selection bias, and smoothed returns (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 returns. Second, fund launches and terminations receive quite some 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, we know the history of the vast majority of ILS funds and, for all of them but one, we were able to obtain return time series starting at inception. Furthermore, we addressed the issue by excluding the past 12 and 24 months from the return series. In contrast to the findings in the hedge fund literature, this even slightly increases the mean return of ILS funds. Hence, we may safely state that backfilling bias is not an issue in our empirical analysis.

[7]The remaining volume is distributed across 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" did neither exhibit a Bloomberg category nor offer additional information. All figures are based on the latest available date. The overall sample starts in January 2001 and ends in December 2015.

Self-selection bias results from the general decision of a manager whether or not to report returns to 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 a 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 (Fermat Capital) decided not to disclose any information at all and is thus missing in our sample (see footnote 3). In addition, we cannot entirely rule out the possibility that we missed some 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 the suspicion of self-selection bias.

Another source of bias may be serially correlated returns, which typically occur due to illiquid exposures (stale prices) in the portfolio of the funds (see, e.g., Getmansky et al., 2004). If present, this issue causes the reported returns to appear smoother than the 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. The reason is that we found a large fraction of the AuM to be invested in cat bonds. For the latter, a quite liquid secondary market exists (see, e.g., Braun, 2016). Therefore, pricing indications are available on a weekly or even daily basis, limiting the smoothed-return 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 the econometric technique by Getmansky et al. (2004).[10]

3 Factor models

3.1 Traditional approaches

First of all, we run a simple asset-class factor model in the sense 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 are summarized in Table 2. All factors are measured as monthly returns in excess of the one-month T-Bill rate.

[10] A related phenomenon are 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). 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-large capitalization stocks (SMB), and high-minus-low book-to-market stocks (HML), as coined by Fama and French (1992). 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. The reason is that 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.[11]

From the hedge fund literature, we adopt the seven-factor approach of Fung and Hsieh (2004), which comprises all Fama and French (1993) factors 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.[12] The hedge-fund-specific factors PTFSBD, PTFSFX, and PTFSCOM have been retrieved from the website of David Hsieh.

[11] 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.

[12] 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* in the following. Formally, the *CAT-CAPM* is defined as:

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

where $CATMKT_t$ and $R^e_{p,t}$ 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.[13] 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. Formally, this idea can be expressed as follows:

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

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. $DEFCOR_t$ 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 con-

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

stituents match those that are usually found in the cat bond market. Moreover, $DEFCAT_t$ represents 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 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 $TERM3Y_t$, $DEFCOR_t$, 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 return 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 $USEQ_t$. In addition, CATMKO2 is therefore a new factor, which 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 U.S. and non-U.S. multi-peril as well as non-U.S. single-peril bonds.[14] 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. Nevertheless, DEFCAT exhibits certain peaks over time, implying that it may have been priced in the past. The means of all other factors are statistically significant positive. Comparing TERM3Y and DEFCOR, 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, DEFCOR, and DEFCAT) in the average monthly return of BBCAT (0.45). The remaining contribution in the *spread*

[14] 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 publicly available.

model equals 0.18 and comes from 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).[15] Table 3 shows the correlation matrix for the ILS-specific factors. Apart from the interpretative benefits the are to be gained from orthogonalizing CATMKT in the multi-factor models, this step is also a statistical necessity, because the excess returns on the cat bond market are relatively highly correlated with USHU and BBCAT. Based on these considerations, we may conclude that multicollinearity is not an issue for the suggested factor model specifications.

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
DEFCOR	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) DEFCOR	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

[15] 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).

4 Empirical results

4.1 Descriptive statistics

We construct equally-weighted indices for all funds, live and dead funds, as well as for each Bloomberg category.[16] Table 5 summarizes the return characteristics of these indices. For comparison purposes, it additionally includes results for a commercially-published ILS Advisers index (also equally-weighted), as well as a popular hedge fund and corporate bond benchmark. Consistent with the literature, we consider the longest available time series for each asset class (see, e.g., Chen et al., 2010). Over the last 15 years, ILS funds have earned an average annual return of 5.64% and exhibited a corresponding return 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. Interestingly, the ILS Advisers Index shows a higher average annual return of 6.31% and a lower volatility of 1.60%. These figures, however, have to be seen 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 more 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 and particularly cat bonds 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. Cat bonds securitize extreme-event insurance risk, i.e., natural disasters with reccurrence periods of 100, 200, 500 or even 1000 years (see, e.g., Smolka, 2006; Swiss Re, 2010). Against this background, even a performance history of 15 years, which covers almost the entire time span during which the ILS market existed, is very short. In fact, the substantial drawdowns that are to be expected following a real 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

[16] Due to the absence of time series data on fund AuM, it is not possible to construct capitalization-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 until 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 until December 2015. The overall sample starts in January 2001 and ends in December 2015.

firms RMS, AIR, and EQECAT. Therefore, historical performance figures as shown in this section should generally be interpreted with utmost caution.

4.2 Time-series regressions

Traditional factor models

Table 7 shows the coefficients for four asset-class models. To avoid collinearity issues 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 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, although the adjusted R-squared does not exceed 0.03 and alpha remains 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.[17]

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.[18] 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). Column (2) contains the results for the *spread model*. We find significant coefficients for all four factors, paired with an insignificant intercept and an R-squared of 0.69. Particularly TERM3Y, DEFCOR, and DEFCAT have a impact on the time series. 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 (3). This model is 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 and particularly

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

[18] On the individual fund level (see next section) we will observe a lot of funds with *CAT-CAPM* betas equal to one, suggesting that their portfolio composition closely resembles the cat bond market portfolio.

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 fitted to our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are Newey and West (1987) corrected 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.

single-peril U.S. earthquake bonds are associated with weaker effects. This is in line with Braun (2016), who finds that the majority of historical primary market issuances were multi-peril cat bonds. Finally, it should be noted that a combination of the *perils model* and the *spread model* does not improve the fit to the time series, since their respective factors are largely buried in CATMKT and thus simply provide a different breakdown of the same variance.

The residuals of the aforementioned regressions as shown in Figure 2 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. For some reason, 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

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 fitted to our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are Newey and West (1987) corrected 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.

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 market portfolio.[19]

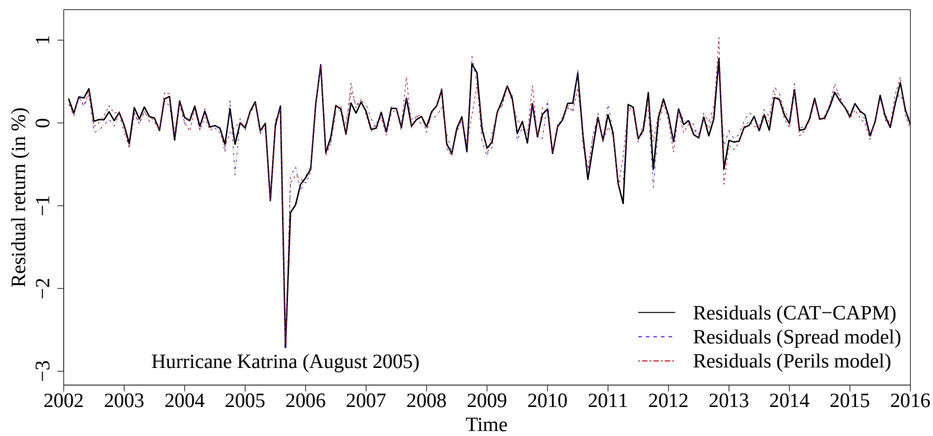
[19] According to Aon Benfield, KAMP Re suffered from an extreme negative return (-78%) in September 2005. Despite its low weight in the market portfolio, this effect is large enough to be captured by CATMKT, CATMKO1, and CATMKO2. Consequently, the corresponding residual in Figure 2 is much smaller.

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 fitted to our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are Newey and West (1987) corrected 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 2: Residuals



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. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels,

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)	
DEFCOR			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 fitted to our ILS fund index. All variables are monthly excess returns. Standard errors in parentheses are Newey and West (1987) corrected 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 until December 2015) into four equally long subperiods and run the *perils model* against the excess return of the aggregate ILS fund index. We also include the Katrina dummy variable during the period July 2005 until December 2008. Table 11 shows the respective results.[20] Our first finding is that 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 risks and single-peril U.S. hurricane risk. However, the single-peril earthquake factor (USEQ) is only significant

[20]Unreported results that underline the robustness of the other two ILS factor models are available from the authors.

Table 11: 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 until December 2008. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

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. The second finding is a much lower explanatory power in the first subperiod (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. The last finding is the significant alpha in the most recent subperiod with an unexplained monthly return of 0.18%. Until the beginning of this time span, the ILS market had already grown substantially. Consequently, the significant abnormal return could be caused by the advent of several non-cat-bond ILS in the fund portfolios, whose return variations are not picked up by our model.

Out-of-sample

To avoid in-sample overfitting, we now test how well our augmented *perils model* and *spread model* explain alternative ILS indices. First, we consider the Eurekahedge ILS Advisers Index introduced in the first part of section four. Second, we turn to the Mercury Investable Catastrophe Risk Index, also known as MiCRIX, which tracks the performance of a diversified portfolio of peak-peril industry loss warranties (ILWs). Both indices start in January 2006. In contrast to cat bonds, ILWs are uncollateralized and unfunded double-trigger contracts, whose main trigger relies on an insurance industry loss index.[21] The results reported in Table 12 indicate that, as expected, the excess returns on the Eurekahedge index can be well described by either approach with adjusted R-squareds of 0.77 for the *perils model* and 0.75 for the *spread model*. Both models, however, display a mediocre fit to the MiCRIX (adjusted R-squareds: 0.58 and 0.57). This suggests that ILW returns share some variation with the cat bond market, yet

[21] For a detailed discussion of ILWs and catastrophe swaps, refer to Braun (2011).

Table 12: Out-of-sample tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Eurekahedge	Eurekahedge	Eurekahedge	Eurekahedge	MiCRIX	MiCRIX	MiCRIX	MiCRIX
CATMKT	0.62***				1.96***			
	(0.11)				(0.55)			
CATMKO		0.30				0.24		
		(0.24)				(1.21)		
BBCAT		0.54***				1.79***		
		(0.11)				(0.49)		
CATMKO1			0.32				0.55	
			(0.24)				(1.13)	
TERM3Y			0.62***				1.92***	
			(0.12)				(0.51)	
DEFCOR			0.54***				1.65***	
			(0.10)				(0.40)	
DEFCAT			0.55***				1.91***	
			(0.11)				(0.44)	
CATMKO2				0.81***				3.01***
				(0.18)				(0.78)
USHU				0.27***				0.89***
				(0.03)				(0.17)
USEQ				0.18***				–0.02
				(0.02)				(0.23)
Constant (alpha)	0.05	0.09	0.08	0.05	–0.46	–0.20	–0.24	–0.31
	(0.09)	(0.06)	(0.06)	(0.05)	(0.47)	(0.44)	(0.38)	(0.27)
Adj. R^2	0.74	0.75	0.75	0.77	0.51	0.53	0.57	0.58
Obs.	120	120	120	120	120	120	120	120

This table shows the coefficients of the *perils model* and the *spread model*. The dependent variable in column (1) and (2) is the return of the Eurekahedge catastrophe bond fund index over the one-month T-Bill rate. The dependent variable in columns (3) and (4) is the return of the Mercury investible Catastrophe Risk Index (MiCRIX) over the one-month T-Bill rate. Standard errors in parentheses are Newey and West (1987) corrected with lags of four. The indices start in January 2006 and end in December 2015. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

other effects are at play as well. Potential differences in the trigger mechanisms, covered territories, reference perils, and securitized loss layers between the cat bond and the ILW market portfolio are likely explanations for these results.

4.4 The cross section of expected excess returns

We now draw on our new factor models to explain differences in the cross section of the expected excess returns of ILS funds. Before addressing each fund individually, we examine the Bloomberg categories using the (augmented) *perils model* as a benchmark. Table 13 shows the respective results. We estimate a negative and significant abnormal return (alpha) for the "Fixed Income" ILS funds, implying that the constituents of this category have underperformed the benchmark during the time period under consideration. In contrast to that, insignificant alphas can be documented for the categories "Alternative" and

Table 13: The cross section of 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) - (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.

"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, 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, which cannot be captured by our risk factors. Finally, the significantly negative alphas for defunct funds reported in the last column of Table 13 suggest underperformance to be the main reason for failure.

Next, we turn to the individual fund level. In the following, 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 section of expected excess returns. We follow Fung and Hsieh (2004) as well as Chen et al. (2010) and only include funds that have at least 24 months of consecutive return data. As a consequence, our sample reduces from 57 to 50 funds.[22]

Table 14 contains the percentage of positive-significant (+), negative-significant (–), and insignificant (0) alphas estimated by means of the ILS-specific factor models. The *CAT-CAPM* (see Panel A) is not able to 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. The corresponding figures for the *spread model* are shown in Panel B. Surprisingly, it results in a higher percentage of significantly positive

[22]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.

alphas (34.00%) and a lower fraction of negative alphas (2.00%) than the *CAT-CAPM*. Despite its better fit to the time series found above, it is thus a much less challenging benchmark for ILS funds. Finally, we focus on the results for the *perils model* as reported in Panel C. Now, the number of funds with significantly negative intercepts rises substantially to 26.00%, implying that a lot more of the managers were in fact unable to earn back their fees. Another 46.00% of the funds exhibit an insignificant alpha. Hence, the *perils model* seems to be the most strict benchmark of the three. Nevertheless, it still leaves the positive expected excess returns of 28.00% of the ILS funds unexplained. This raises the question whether approximately one quarter of all funds were lucky, indeed able to outperform the market for cat bonds, or whether their alphas stem from other (traditional or exotic) risk exposures that are not captured by our ILS-specific factor models. We will further deal with this question in the next section. A last observation to be pointed out here, is 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 consistent result is another indication that those managers, which ceased operations were 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 possessing less wiggle room to generate alpha returns.

In Figure 3, 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.[23] 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 not larger than those of their peers with lower betas. Moreover, all funds with significantly positive alphas (based on the *CAT-CAPM*) have a beta exposure below 0.85. Again, this is an indication for manager skill, luck, or additional holdings of non-cat-bond ILS or other asset classes.

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

Table 14: 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

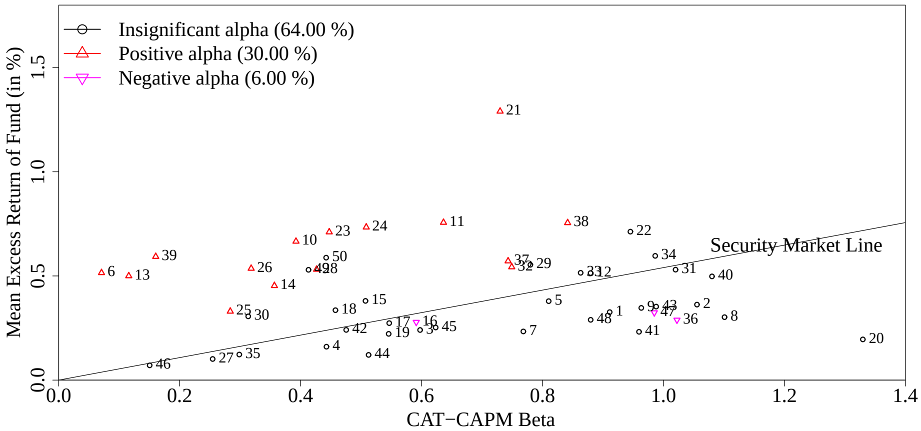
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Ratings model	Index	Fund category			Status	
Alpha distr.	All Funds	Alternative	Fixed Income	Other	Live	Dead
+	36.00%	29.41%	15.38%	55.00%	45.00%	0.00%
0	64.00%	70.59%	84.62%	45.00%	55.00%	100.00%
−	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
No. of funds	50	17	13	20	40	10

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. The time period for each individual fund ranges between January 2002 and December 2015.

Figure 3: CAT-CAPM beta representation

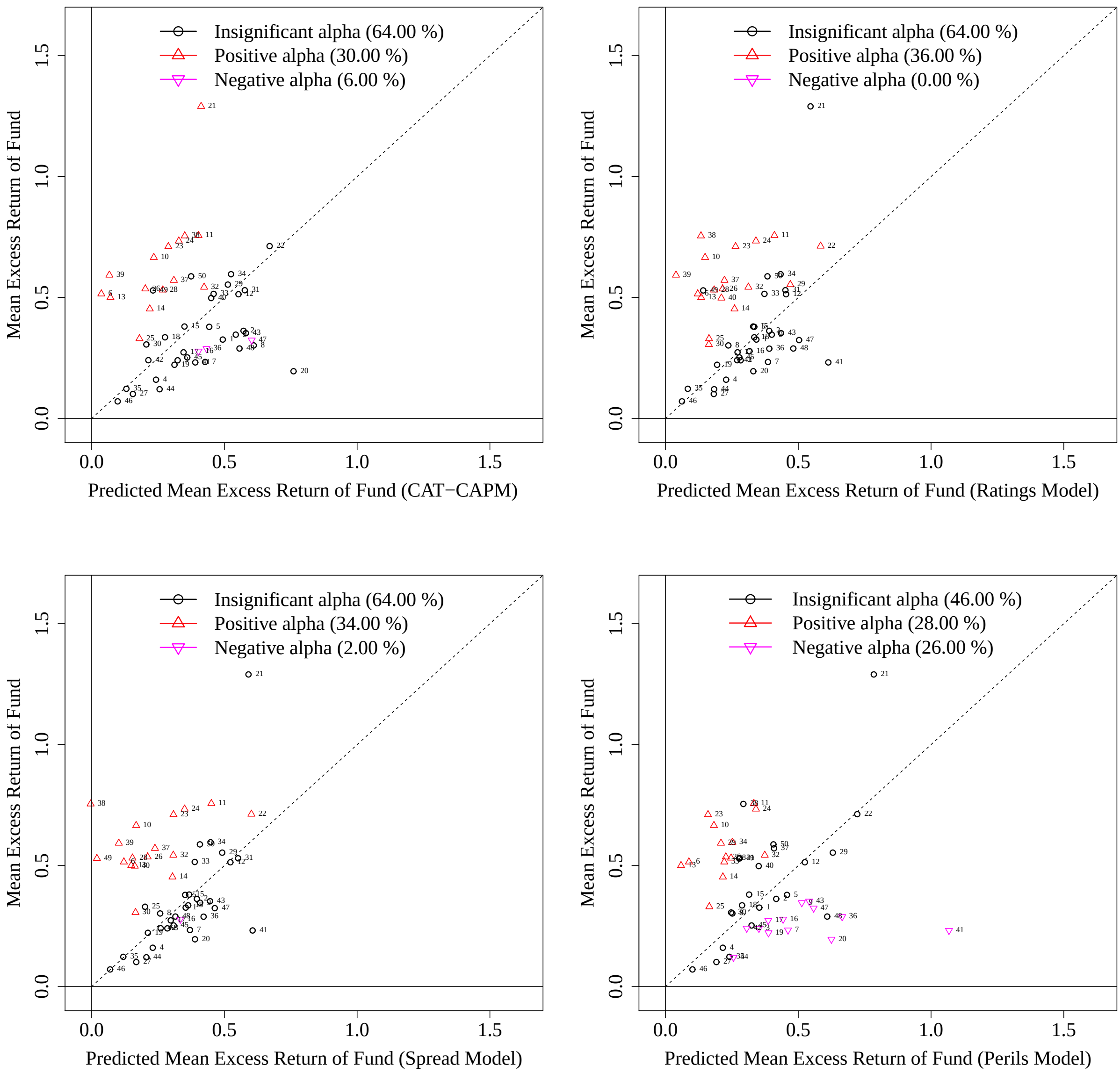


This figure illustrates the actual mean excess returns of 50 ILS funds against their beta estimated by the *CAT-CAPM*. Black circles indicate insignificant alpha values. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant 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.

Figure 4 illustrates the cross-sectional results by plotting the actual mean excess returns against the mean excess return predicted by four ILS-specific factor models. In the absence of significant abnormal excess returns, all funds should concentrate along the dotted 45-degree line. Yet, both for the *CAT-CAPM* 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 identify both significantly positive or negative alphas of ILS funds.

Overall, we are able to single out the *perils model* as the most challenging benchmark. Nevertheless, about one quarter of all ILS funds exhibits positive expected excess returns that cannot be explained by any of the four approaches. We consider this to be a relatively large fraction. A similar percentage is found by Capocci and Hübner (2004), who study the performance of hedge funds. However, their model is hardly tailored to the specific characteristics of those alternative investment vehicles. Many other studies report a much lower fraction of abnormal returns. Dahlquist et al. (2000), e.g., measure the performance of Swedish mutual funds by means of an asset-class factor model and Eling and Faust (2010) apply a hedge-fund-specific factor model in emerging markets. In both cases, less than ten percent of the managers exhibit significant alphas.

Figure 4: 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 *spread model* (upper right), and the *perils model* (bottom). Black circles indicate insignificant alpha values. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant 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.

4.5 Performance attribution

Exposure to ILWs

In this section, we want to further investigate whether the 28% of ILS funds that outperformed our *perils model* are in fact skilled fund managers. If some of the funds invest in traditional asset classes, we would measure an outperformance, since the *perils model* does not control for such an exposure. 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 significant alphas might be positions in non-cat-bond ILS that are not captured by the *perils model*. Return indices for such instruments are generally unavailable, the only exception being ILWs. For the latter, we can draw on the excess returns of the MiCRIX, which we have already employed in our out-of-sample tests. Thus, we integrate the variable $MiCRIX_t$ into the *perils model* and define the resulting extended *perils model* as:

$$R^e_{p,t} = \alpha + \beta_{p,1} CATMKO2_t + \beta_{p,2} USHU_t + \beta_{p,3} USEQ_t + \beta_{p,4} MiCRIX_t. \quad (5)$$

As shown in Table 15, the positive abnormal returns 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 the *perils model* revealed in ILS funds.

Table 15: 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 14. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Fund characteristics

Another determinant of the differences in performance could be fund characteristics. To test this notion, we draw on the natural logarithm of current AuM, performance fees, load fees, as well as fund age, defined as the natural logarithm of active years. We do not include the expense ratios, top ten holdings, and cash reserves, as these figures are available for no more than 25 funds.[24] We run a single cross-sectional regression of each fund's alpha (based on the *perils model*) on these independent variables. The sample size is determined by the number of funds for which we have access to the necessary data. Table 16 shows the respective results.

Table 16: 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.

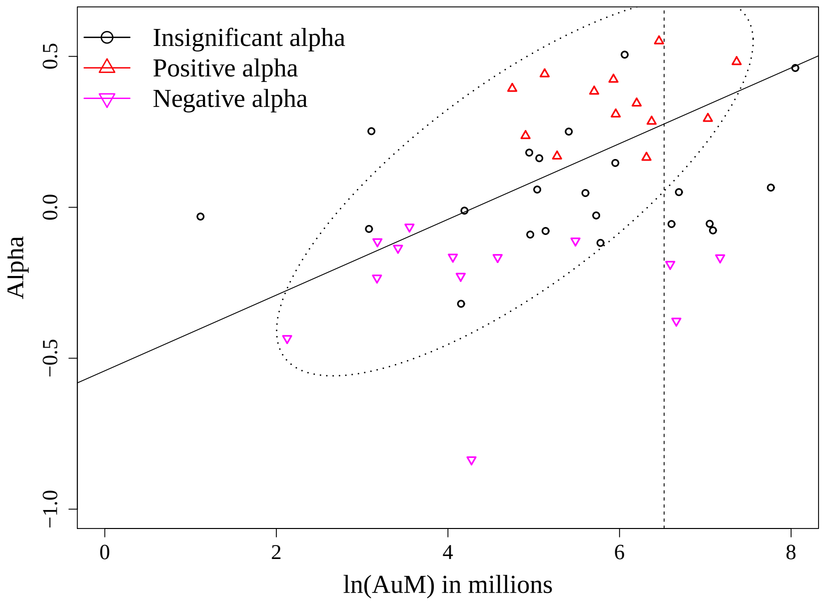
As opposed to Chen et al. (2004), who demonstrate that size erodes the performance of mutual funds, we find a significant and positive relationship between AuM and abnormal returns. This also contradicts evidence from the hedge fund industry (see, e.g., Ammann and Moerth, 2005).[25] Figure 5, in which 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, the relationship under consideration seems to be nonlinear, suggesting that there might be an optimal size for ILS funds. However, a sound theoretical basis for the direction of causality with regard to this effect is difficult to establish. To put it differently, does size cause performance or vice versa? In the first case, larger funds could be able to 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 to access other types of ILS, which are more complex to handle than cat bonds. On the contrary, they might suffer from diseconomies of 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, smaller funds could be small because their under-

[24]Unreported results showed no significant impact of these three variables.

[25]Obviously, we have to carefully interpret this finding, since our fund information is not a time series but a single cross section at the end of the sample period.

performance repels investor capital. Ultimately, however, one relevant take-away upholds. Our *perils model* tends to consistently identify smaller funds as underperformers and larger funds as outperformers. Apart from fund size, only the performance fee exhibits a consistently significant coefficient. According to the last column of Table 16, a 100 basis point increase in the performance fee implies an additional abnormal return of 19 basis points. This is an indication for effective incentivization.

Figure 5: 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 680mn in AuM. The vertical black line (dashed) indicates a break in the functional relationship between alpha and fund size at USD 680mn. Red upward pointing triangles indicate significant positive alphas at the 10%-level. Magenta downward pointing triangles indicate significant negative alphas at the 10%-level.

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 whether a particular subset of ILS funds was able to generate positive abnormal returns in the past.

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 are 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 abnormal returns for one quarter of all ILS funds. These alphas exhibit a significant relationship with fund size and performance fees. However, it is challenging to attribute them to manager skill, luck, or exotic beta exposures originating from non-cat-bond ILS.

A few limitations of our work constitute the basis for future research. Although the market has already been cautiously 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, even the 15 years of available time series data are no more than the blink of an eye. It therefore remains unclear what level of expected excess returns investors can expect in the long run. The question whether the risk premium offered by ILS is adequate relative to other asset classes can only be answered in a meaningful way by running a simulation-based performance analysis using a commercial catastrophe risk model. Apart from that, future research could aim at extending the perils model by further cat-bond risk factors. In its current form, the approach 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 models could be complemented with factors that capture the returns of non-cat-bond ILS, such as collateralized reinsurance, ILWs, 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. For this purpose, the previously discussed model extensions could be combined with an analysis of persistence in the fund performance.

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