Portfolio Diversification Effects of Catastrophe Bonds
Preliminary and Incomplete

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Abstract

This paper demonstrates that catastrophe (cat) bonds provide substantial benefits of diversification when added to an investor's opportunity set already consisting of securities from traditional asset classes. We find that cat bonds significantly reduce drawdown measures and tail risk under various market regimes while still enhancing risk-adjusted returns. We estimate GARCH-DCC models and find a low average correlation between cat bonds and traditional asset classes. We then conduct rigorous out-of-sample portfolio analysis using four different asset-allocation models of varying levels of estimation risk. This analysis shows superior performance compared to a dynamic and optimized benchmark portfolio. Finally, we conduct mean-variance spanning tests and provide further compelling evidence that portfolios including cat bonds lie outside of the mean-variance frontier attainable by portfolios holding traditional asset classes alone.

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1 Introduction

Insurance-linked securities (ILS) are a relatively recent financial innovation allowing risk transfer from the insurance industry to the financial markets. Pension funds, banks and sovereign wealth funds are the largest holders of ILS, and several hedge funds have recently been started to specialize in managing portfolios of ILS (Woodall (2013)). Catastrophe (cat) bonds make up the largest segment of the ILS market. The cat bond market has grown significantly since the first issuance in 1994 as illustrated in Figure 1. Typically, cat bonds are sponsored by insurance companies or other entities to protect against catastrophe losses including natural disasters and extreme risks such as adverse mortality arising from pandemics. cat bond risk capital outstanding by risk or peril trigger type is shown in Figure 1.

Cat bonds are sponsored by the entity desiring protection, structured by a third party such as a reinsurer and then sold to investors. The capital raised from investors is used to fund a special purpose vehicle (SPV) which holds high quality, low risk securities. The sponsoring entity makes coupon payments and, if the bond matures without a triggering event, the principal amount is returned to investors. However, if a triggering event occurs the sponsoring entity can access the capital in the SPV to pay claims, after which the remaining coupon and principal payments of the bond are curtailed.

Several cat bonds have been triggered in recent years by naturally occurring and man-made events. Hurricanes Katrina (2005) and Ike (2008) resulted in some loss of principal while the 2011 Tohoku earthquake and severe thunderstorms in the United States resulted in total losses for three cat bonds and a partial loss for a fourth. The Lehman Brothers collapse in 2008 resulted in technical partial defaults for four issues in which Lehman Brothers was the total return swap counterparty.[1] Similarly, the uncertainty surrounding the U.S. debt-ceiling crisis in early 2014 caused technical defaults for two bonds with one realizing a minimal loss of $28,375 upon maturity in August 2014 due to the sustained loss of value of collateral.

From January 2006 to December 2014, the Eurekahedge ILS index shows negative returns in only seven out of 108 months. Interestingly, the largest negative monthly return, -3.94 percent, occurred in March 2011, the same month as the Tohoku earthquake. The second largest loss was

[1] http://www.artemis.bm/blog/2008/09/30/lehman-brothers-related-cat-bonds-downgraded-by-sp

-0.74 percent in September 2008 followed by the third largest loss, -0.57 percent in October 2008.[2]

Since the values of insurance-linked securities are contingent on events such as natural disasters, it is generally thought that catastrophe bonds are relatively uncorrelated with financial risk factors. Consequently, cat bonds are generally considered to bring diversification benefits to portfolios consisting of securities from other asset classes. The purpose of this paper is to rigorously study this claim. We analyze the diversification benefits of cat bonds in four different ways. From each perspective, we find strong support for the notion that cat bonds provide substantial diversification benefits when added to an investment opportunity set already consisting of traditional asset classes.

First, consistent with prior literature, we examine the dynamic correlation properties of cat bonds with other asset classes. We estimate generalized autoregressive conditional heteroskedasticity (GARCH) dynamic conditional correlation (DCC) models of cat bond returns with returns of other traditional asset classes. GARCH-DCC models were introduced and popularized by Engle and Sheppard (2001) and Engle (2002). This analysis illustrates that dynamic conditional correlations of cat bond returns with returns of other asset classes are typically low, suggesting that cat bonds may provide additional diversification benefits when included in already diversified portfolios.

Second, we find large and persistent portfolio diversification benefits of cat bonds in rigorous out-of-sample analyses. To do this, we compare the performance metrics of benchmark portfolios consisting only of securities from traditional asset classes to the performance of portfolios consisting of both traditional assets and cat bonds. We perform such comparisons for portfolios formed using four different asset-allocation models. The asset-allocation models we consider are the naive $1/N$ model, the Markowitz mean-variance model, the minimum variance model, and the volatility-timing model. These models capture much of the recent development in the portfolio optimization literature addressing estimation risk, turnover, and low volatility anomalies.

Third, we conduct the mean-variance spanning tests originally introduced by Huberman and Kandel (1987) and recently summarized by Kan and Zhou (2012). Our results strongly indicate that the time series of payoffs of cat bonds cannot be replicated in mean-variance space by portfolios holding only other asset classes.

Finally, we consider this performance amongst various market regimes and study the tail risk of our cat bond portfolios. We find that cat bonds add substantial diversification benefits during

[2] http://www.artemis.bm/eurekahedge_ils_advisers_insurance_linked_securities_fund_index/

the recent financial crisis and reduce drawdown measures and conditional value at risk during times of market distress.

For both the DCC analysis and the portfolio diversification study, we consider the traditional asset classes represented by U.S. equities, international equities, bonds, commodities, and real estate. We use index proxies for these asset classes given by the Standard and Poor's 500 Index (SPX), Morgan Stanley Capital International All Country (ex US) World Index (ACWX), Barclays Aggregate Bond Index (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). We use the Swiss Reinsurance (SwissRe) Global Cat Bond Total Return Index (SRGLTRR) as our proxy for cat bonds. In our analysis, we use weekly data for each index over the time period January 2000 through October 2014. All data are obtained from Bloomberg. [3]

This paper makes a number of contributions both to the insurance-linked securities literature, as well as to the literature on testing asset allocation strategies. This is the first paper to rigorously examine the dynamic correlation properties of cat bonds with a broad set of asset classes consisting of U.S. equities, international equities, bonds, commodities, and real estate. In addition, this paper also introduces novel approaches to investigating the diversification value of specific asset classes through rigorous out-of-sample tests. We provide a benchmark suite and a new standard of analyses and methodologies to study the diversification benefits of a candidate asset class.

The remainder of this paper is organized as follows. In Section 2, we review the literature on the risk and return of cat bonds, as well as the correlation of cat bond returns with returns of other asset classes. In Section 3 we describe our data, models, and methodologies. In Section 4 we present our results and Section 5 concludes.

2 Literature Review

Returns from exposure to catastrophe risk became a topic of research in the mid- to late-1990s. At that time data was limited and researchers developed proxies to examine the correlation of catastrophe risk with other assets using data prior to 1998. In general, catastrophe risk was found to be uncorrelated with risk from other asset classes and cat bonds were therefore identified as

[3] The SwissRe Global Cat Bond Total Return Index (SRGLTRR) was started in January 2000.

having zero beta. Specifically, Froot, Murphy, Stern, and Usher (1995) use pricing and claims data from more than 2,000 reinsurance contracts from 1970 to 1994 to estimate returns for catastrophic risk. These returns proxy those investors would have received if they had supplied the capital for these contracts.

A comparison of the correlation of returns among assets reveals that cat bonds, as proxied by cat risk, are not correlated with the other asset classes supporting the belief that cat risk has zero beta. Specifically, Froot et al. (1995), finds returns from cat risks are negatively correlated with the S&P 500 and U.S. government bonds with insignificant estimates of -0.13 and -0.07, respectively. They are positively, but again insignificantly, correlated with international bonds and the EAFE index with estimates of 0.21 for both. In comparison, the correlation estimates amongst the other assets classes are higher and significant with estimates of 0.40 for U.S. stocks and bonds, 0.45 for international stocks and bonds and 0.58 for international stocks and U.S. stocks.

Litzenberger, Beglehole, and Reynolds (1996) use the PCS aggregate loss index and earned premiums from lines that typically insure and pay claims during catastrophes to develop historical loss ratios and estimate expected returns from catastrophe risk. They compare these returns with the S&P 500 and a government bond index using data from March 1955 to December 1994 and find small and insignificant correlations of 0.058 and 0.105, respectively. They conclude investment in catastrophe risk may be attractive due to the implied zero-beta with historical stock and government bond return. Cantor, Cole, and Sandor (1997) also find cat experience is uncorrelated with capital markets and securitizations of such are zero-beta assets.

Hoyt and McCullough (1999) are the first to examine actual trades by using PCS Catastrophe Insurance Options from September 1995 to March 1997. They find no correlation supporting the findings of Froot et al. (1995) and Cantor et al. (1997). They also examine quarterly data for cat loss exposures from 1970 to 1995 and find no correlation with financial markets. They examine separate time periods to account for increased catastrophic exposure beginning in 1989 when seven of the ten worst catastrophes during the study period occurred and confirm no correlation is found.

Recent studies beginning in 2009 and including data during the financial crisis period find results similar to the earliest studies when the market is performing normally. However, when the market is in financial crisis or a major catastrophe such as Hurricane Katrina has occurred, recent studies find increases in correlation between cat bond returns and returns from other asset classes.

Cummins (2008) use the Swiss Re Cat Bond BB index to examine correlation of Cat bonds with the Merrill-Lynch BBB corporate bond index, Barclay's CMBS index, the S&P 500 and the 3 month LIBOR and 3 US government bond yield rates. They examine data from two time periods. Data from January 2002 to June 2007 is considered to be from normal market conditions while data from July 2007 to January 2, 2009 is considered to be from the financial crisis period. They find during normal, or non-financial crisis market periods there is no correlation between cat bond returns and other asset classes and cat bond returns are cost to zero beta with total returns from stock and bonds. However, during the subprime crisis, cat bond total returns were significantly correlated with the Merrill Lynch BBB corporate bond index and the S&P 500 index.

Gurtler, Hibbeln, and Winkelvos (2012) examine secondary market cat bond premiums obtained from Lane Financial, LLC from the second quarter of 2002 through 2012 and the Guy Carpenter Global Property cat rate on line index. They find dependency between the cat bond and capital markets with greater dependency during the financial crisis. They also find the Lehman Brothers bankruptcy and Hurricane Katrina affected cat bond pricing however, Katrina only affected premiums for the wind peril.

Similarly, Carayannopoulos and Perez (2015) examine the returns of cat bonds, stocks, corporate bonds and government bonds and find cat bonds are zero-beta assets only during non-crisis periods. During the recent financial crisis cat bonds were correlated with the returns of other assets. However, cat bonds were not as affected by the crisis as other assets. Interestingly, they find the financial crisis had a greater impact on correlation than Hurricane Katrina, the most expensive insured natural disaster to date. Further, they find evidence that the effects of the financial crisis on cat bonds are gone by 2011 at which time correlations with other asset classes return to pre-crisis levels.

Two studies also specifically focus on actual returns. Froot et al. (1995) compared returns from catastrophe risk to U.S. and international stocks and bonds as well as an international stock index consisting of European, Asian and Far East (EAFE) stock indices. Froot et al. (1995), find returns for cat risk are less than those for domestic stocks, higher than domestic bonds and less volatile than both. In the event of a serious event they can be substantially, negatively impacted.

Thomann (2013) uses daily return data on P&C insurer stocks and a stock market index from 1988 to 2006 to examine the effect of catastrophes on insurer stock volatility. Hoyt and McCullough

(1999), Thomann's study includes the ten most expensive insured catastrophes current as of his study. He finds the terrorist attack of September 11, 2001, (9/11) shifted the beta for insurance stocks. Further, catastrophic events increase the volatility of insurer stocks immediately after and within several days of the event. With the exception of 9/11, catastrophic events reduce the correlation between insurer stocks and the market.

3 Data and Methodology

To examine the potential benefits of diversification of cat bonds we consider the SwissRe Global Cat Bond Total Return Index (SRGLTRR) in a portfolio with five other diverse asset classes. These asset classes are: (1) the Standard and Poor's 500 Index (SPX) to capture large cap US equities, (2) the MSCI ACWI ex US Index (ACWX) to measure large, mid and small cap size segments across style and sectors in non-US Developed and Emerging Marktes, (3) Barclays Aggregate Bond Index (AGG) to gain exposure to the Fixed Income universe, (4) the Deutsche Bank Liquid Commodity Index (DBLCI) and the Dow Jones Real Estate Index (DJRE). There are of course many other potential assets classes that could be included but this short list met our needs of diversity and coverage. Our data spans from January 2002 through September 2014 coinciding with the availability of the SwissRe Global Cat Bond Total Return Index (SRGLTRR). We measure returns at a weekly level yielding 748 weekly returns for each of the six asset classes.

3.1 Dynamic Conditional Correlations

To assess diversification potential of cat bonds we examine their dynamic correlation properties with the other asset classes. We implement a standard GARCH(1,1) DCC-GJR model of Engle and Sheppard (2001). Details on the GARCH-DCC estimation methodology can be found in the Appendix. We find dynamic conditional correlations of cat bonds with other asset classes are typically low as illustrated in Figure 2. A notable exception was during the financial crisis of 2008, when the correlations of cat bonds with US equities, international equities, bonds, and commodities spiked to levels in the 0.35 to 0.5 range. Interestingly, the correlation with real estate remained below 0.2 during this period. These findings suggest that cat bonds may provide additional diversification benefits when included in portfolios of other assets.

3.2 Methodology for the Out-of-sample Analysis

Next we compare the performance metrics of "benchmark" portfolios consisting only of traditional assets to the performance of portfolios consisting of both traditional assets and cat bonds. We use two different approaches to construct our out-of-sample returns and perform such comparisons for portfolios formed using four different asset-allocation models.

Our first approach is straightforward and is consistent with the risk and return changes an investor would experience by adding this asset class to an existing portfolio. For this case we simply compare the out-of-sample portfolio statistics of a benchmark portfolio consisting of the five traditional asset classes with a portfolio consisting of the five traditional asset classes plus cat bonds. We repeat this analysis using each of the four asset-allocation models.

Our second approach accounts for the implicit bias of our first approach. Specifically the first approach compares portfolios containing five assets to portfolios containing six assets. Considering all our indices are sufficiently diversified and of comparable levels of risk, adding any other representative asset class will have diversification benefits as portfolio variance is a monotonically decreasing, and convex function of the number of assets. To implement this approach we construct our test portfolios as an equally weighted portfolio of five portfolios. Each portfolio includes the SwissRe Global Cat Bond Total Return Index (SRGLTRR) and alternates four of the five indices from the benchmark portfolio. This construction eliminates the bias that diversification benefits increase with the number of assets since each test portfolio now contains only five assets. We feel this test provides a rigorous out-of-sample environment and also find the results are similar.

3.3 Asset-Allocation Models

Let R_t denote the N-dimensional vector of excess returns on the N risky assets available for investment at time t. μ_t is an N-dimensional vector of expected excess returns on the risky assets. All excess returns are in excess of the risk-free rate. Σ_t denotes the $N \times N$ variance-covariance matrix of returns. The sample counterparts for the expected returns and variance-covariance matrix of returns are $\hat{\mu}_t$ and $\hat{\Sigma}_t$ respectively. We do not allow short-sales and do not allow leverage to produce robust results consistent with the findings of Jagannathan and Ma (2003). The authors find that even imposing the wrong constraints in a portfolio optimization context can help performance due to the reduction in estimation error. Each of our models can be classified under a broader heading of a "plug-in" approach. This name is derived from the fact that we estimate moments of the returns and simply "plug-in" these estimates to well-known solutions of a given optimization problem.

3.3.1 Estimating the Moments

To estimate the conditional moments we employ the common rolling-sample approach of (?, ?). For $t > L$, our estimates are $\hat{\mu}_t = 1/(t-L)\sum_{i=0}^{t-L-1} r_{t-i}$ and $\hat{\Sigma}_t = (1/(t-L))\sum_{i=0}^{t-L-1}(r_{t-i} - \hat{\mu}_t)(r_{t-i} - \hat{\mu}_t)'$. We use the entire sample each period beginning with a burn-in window of length L. We set $L = 60$ consistent with (Demiguel, Garlappi, & Uppal, 2009). This methodology provides the largest possible sample for each estimation window thereby reducing sampling error.

3.3.2 The Models

We use four distinct portfolio selection models to assess diversification effects under various levels of estimation risk. We use the Markowitz mean-variance model (the most estimation risk), the minimum variance model (2nd most estimation risk), the volatility-timing model ((Fleming, Kirby, & Ostdiek, 2001; Fleming & Kirby, 2003), 3rd most estimation risk), and the naive $1/N$ model (no estimation risk). Demiguel et al. (2009) and Tu and Zhou (2011) have recently popularized the strong relative performance of the naive $(1/N)$ strategy. These studies find that naive diversification is particularly attractive because it involves no estimation error, no optimization, no matrix inversion, no shorts, and extremely low turnover. The implication is that expected returns are proportional to total risk rather than systematic risk. Mathematically this model imposes the restriction that μ_t is proportional to $\Sigma_t e$ for all t where e is a conformable vector of ones.

In direct contrast to the naive $(1/N)$ strategy we employ the standard Markowitz mean-variance model, the global minimum variance model, and the volatility timing model. The Markowitz mean-variance model requires the estimation of both the conditional mean vector and the conditional covariance matrix while the global minimum variance model ignores the conditional mean estimates. Jagannathan and Ma (2003) find imposing short-sale constraints on the minimum-variance portfolio shrinks the largest eigenvalues in the system reducing estimation risk while providing the best performance in terms of Sharpe ratios. To further reduce estimation risk we also consider a minimum variance model incorporating an extreme version of shrinkage estimation, (Fleming et al., 2001; Fleming & Kirby, 2003; Kirby & Ostdiek, 2012). These strategies are referred to as "volatility-timing" strategies and they significantly outperform mean-variance efficient portfolios. Specifically Kirby and Ostdiek (2012) restrict the covariance matrix of excess returns to be diagonal thereby requiring no estimation of conditional covariances. Detailed derivations of the optimization problems associated with these models are in the Appendix.

3.4 Mean-Variance Spanning Tests

We use the mean-variance spanning tests originally introduced by Huberman and Kandel (1987). The null hypothesis of these tests is that an asset's payoffs can be spanned or replicated in mean-variance space by a set of K benchmark assets. [4] Statistically the test begins with the following regression:

$$r_{test,t} = \alpha + \sum_{i=1}^{K} \beta_i bench_{r,i,t} + \epsilon_t \tag{1}$$

The spanning hypothesis becomes the following set of linear parametric restrictions on the model,

$$H_0: \ \alpha = 0, \ \sum_{i=1}^{K} \beta_i = 1 \tag{2}$$

As in Ferson, Foerster, and Keim (1993) we test these restrictions using a Wald test under conditional heteroscedasticity. We use the GMM estimator of Hansen (1982) as recommended by Kan and Zhou (2012). Since both the model and the constraints are linear, the GMM version of the likelihood ratio test, the Lagrange multiplier, and the Wald test are numerically identical. We provide details of the statistical inference for GMM tests in the next section. For the moment conditions we use the standard first-order conditions of OLS defined as $x_t = [1, R'_{bench,t}]'$, $\epsilon_t = R_{test,t} - B'x_t$. The moment conditions used for the GMM estimation of B are:

$$E[g(R_t, \theta)] = E[x_t \otimes \epsilon_t] = 0_{(K+1)N} \tag{3}$$

[4] Kan and Zhou (2012) provide a comprehensive summary all of the subsequent developments of mean-variance spanning tests under various applications.

3.5 Statistical Inference

To conduct statistical inference about the relative performance of our various strategies we follow Kirby and Ostdiek (2015) and use large sample t and χ^2 statistics. We compute these statistics using the generalized method of moments (GMM). Hansen (1982) uses the Delta method, Slutky's theorem and LLN to derive the asymptotic distribution of the GMM estimators. Recent asymptotic distribution derivations for Sharpe ratios are also provided by Opdyke (2007) and Bailey and de Prado (20011) who use these theorems in their derivations. However we use GMM standard errors to appeal to these more recent derivations while still being applicable in a more general context. We begin with a set of moment conditions of the form $E(g(R_t, \theta)) = 0$, where $g(R_t, \theta)$ is a $J \times 1$ vector of moments, analogous to disturbances, R_t is a vector or returns, and θ is $J \times 1$ vector of parameters. We use the fundamental result from Hansen (1982) that, subject to general conditions, the limiting distribution of $\hat{\theta}$ is given by:

$$\sqrt{T}(\hat{\theta} - \theta) \xrightarrow{d} N(0, V) \tag{4}$$

We have the following: $V = D^{-1}SD^{-1'}$, $D = E(\partial g(R_t, \theta)/\theta')$,and $S = \sum_{-\infty}^{\infty} E(g(Y_t, \theta)g(Y_{t-j}, \theta)')$. Our moment conditions are specified as follows:

$$g(R_t, \theta) = \begin{pmatrix} R_{bench,t} - \sigma_{bench} \times SR_{bench} \\ R_{test,t} - \sigma_{test} \times SR_{test} \\ (R_{bench,t} - \sigma_{bench} \times SR_{bench})^2 - (\sigma_{bench})^2 \\ (R_{test,t} - \sigma_{test} \times SR_{test})^2 - (\sigma_{test})^2 \end{pmatrix} \tag{5}$$

Using equation (4) the asymptotic standard errors of the Sharpe ratios allows us to conduct a Wald test of linear restrictions to determine if the differences between the Sharpe ratios of our benchmark and test portfolios are statistically different from zero. We consider the following test statistic:

$$(\widehat{SR}_{test} - \widehat{SR}_{bench})(R'_{SR} V R_{SR})^{-1}(\widehat{SR}_{test} - \widehat{SR}_{bench}) \sim \mathcal{X}^2(1) \tag{6}$$

In equation 6, the discrepancy vector $R_{SR} = (-1, 1, 0, 0)$ and V is the asymptotic covariance matrix described in equation 4. The square root of this statistic is equivalent to the following limiting distribution:

$$\sqrt{T}((\widehat{SR}_{test} - \widehat{SR}_{bench}) - (SR_{test} - SR_{bench}) \xrightarrow{d} N(0, R_{SR} V R'_{SR}) \tag{7}$$

In the case where the population Sharpe ratios are equal in our benchmark and test portfolios we have the following large-sample test statistic:

$$\sqrt{T}\left(\frac{\widehat{SR}_{test} - \widehat{SR}_{bench}}{(R_{SR}\hat{V}R'_{SR})^{1/2}}\right) \overset{\text{asy}}{\sim} N(0,1) \tag{8}$$

3.5.1 Regime Analysis

To obtain a comprehensive understanding of the performance of ILS portfolios, we test multiple subsets of our sample. We define our entire sample from Jan 2002 - Sep 2014 as **Whole Sample**. We define the NBER dated recession (Dec 2007 - June 2009) sample period as **Recession**. We define two other subsets, Bullish and Bearish, to examine the performance of our portfolios during the tails of the market. **Bullish (Bearish)** markets are defined as periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. Assessing performance during the recent recessions allows to view the diversification benefits when nearly all assets classes were suffering. Assessing performance during the **Bullish (Bearish)** markets allows to view the benefits of diversification during the best and worst time period of the market.

4 Results

4.1 Summary Statistics

We present annualized summary statistics for the returns of the 6 asset classes in Tables 2 and 3, for all regimes. In the whole sample the mean returns of the indices are not materially different ranging from 4.3% to 7.35% per year. In contrast, the standard deviation and Sharpe ratio of the cat bond index are significantly different. Notably, the cat bond index displays extreme kurtosis and has the longest left tail. Further, the Calmar ratios of the cat and AGG indices, 1.2073 and 1.2542 respectively, are more than four time bigger than the others.

The true value of the diversification benefits of the cat bond index becomes apparent during the recession and bear markets. The mean return of the cat bond index is 3.68% compared to the SPX mean return of −24.5%. Further, the volatility of the cat bond index is relatively unchanged while the volatility of the other asset classes becomes much larger. The statistics are even more dispersed during the Bear markets. cat bond mean returns are 2.15% compared to −122.86% for the SPX and −121.09% for the RE index. The low volatility profile of the cat bond index is also preserved during Bull markets as the mean return underperforms all assets classes except for the bond index, AGG.

4.2 Dynamic Conditional Correlations

Dynamic Conditional Correlation estimates find, in general, cat bond returns relatively uncorrelated with the returns of the other asset classes. The dynamic condition correlations over time are illustrated in Figure 2. The mean correlation over the whole sample is 0.0399 for SPX , 0.0447 for AGG, 0.0343 for CMDT, −0.0068 for RE, and 0.0902 for ACWX. During the recent financial crisis the correlations of cat bonds with US equities, international equities, bonds, and commodities spiked to levels in the 0.35 to 0.5 range during some weeks. However, mean correlations during the NBER recession show that cat bonds remained relatively uncorrelated with the other asset classes with mean correlations of 0.1104 for SPX , 0.1137 for AGG, 0.1670 for CMDT, −0.0172 for RE, and 0.2035 for ACWX. These low correlations provide evidence of large diversification benefits when added to portfolios of traditional assets. These effects are even more pronounced in our out-of-sample analysis.

4.3 Out-of-Sample Tests

For each of the $T - L$ computed moments we implement our portfolio strategies and end up with a vector of out-of-sample portfolio returns of size $T - L \times 1$. We compute summary statistics as well as out-of-sample Sharpe ratios, estimates with the Fama and French four-factor asset pricing model augmented with three bond market factors, the information ratio (IR ratio), and portfolio turnover. The Sharpe ratio is the sample mean of the out-of-sample excess returns, $\hat{\mu}_i$ divided by the sample standard deviation, $\hat{\sigma}_i$

$$\widehat{SR}_i = \frac{\hat{\mu}_i}{\hat{\sigma}_i} \tag{9}$$

We use the GMM standard errors to compute the probability that the Sharpe ratio is greater than zero and the p-value of the Wald statistic to test that the Sharpe ratio from our test portfolio and benchmark portfolio are statistically different. We report reward-to-risk ratios which are identical to Sharpe ratios except raw returns are used in lieu of excess returns.

To examine the amount of trading required to implement each strategy we use a method similar to (Demiguel et al., 2009) to compute the turnover of each portfolio strategy. For each strategy and dataset we take the average sum of the absolute value of the trades across the N available assets. Letting i reference each of the N assets, numerically the computation is as follows:

$$Turnover = \frac{1}{T-t} \sum_{t=1}^{T-t} \sum_{i=1}^{N} |\hat{w}_{i,t+1} - \hat{w}_{i,t^+}| \tag{10}$$

We define $\hat{w}_{i,t}$ as the portfolio weight in asset i at time t; $\hat{w}_{i,t^+}$ is the portfolio weight before re-balancing at time $t+1$; and $\hat{w}_{i,t+1}$ is the desired portfolio weight at time $t+1$, after re-balancing. To compute $\hat{w}_{i,t^+}$ we must consider the mechanical changes that occur within the portfolio. Assets that have done well over the time period will make up more than their starting share of weight at the end of the period, and assets that have done poorly will make up less than there starting share. We compute $\hat{w}_{i,t^+}$ as:

$$\hat{w}_{i,t^+} = \frac{\hat{w}_{i,t}(1 + r_{i,t})}{1 + \sum_{i=1}^{N} \hat{w}_{i,t} r_{i,t}} \tag{11}$$

Even with naive diversification, $w_{i,t} = w_{i,t+1} = 1/N$, but w_{i,t^+} may be different simply due to changes in the asset prices between time t and time $t+1$.

To assess risk-adjusted performance we use the Fama and French (1993)three factor asset pricing model with the Carhart (1997) momentum factor and three bond market factors as recommended by **(Steve insert reference here)**. We estimate the information ratio (IR), computed as the alpha from the factor regression divided by the standard deviation of the residuals, also known as the tracking error or idiosynchratic volatility (IVOL). This idiosynchratic reward to idiosynchratic risk measure is similar to the Sharpe ratio except that the expected return from the Sharpe ratio is replaced with the expected return from a factor model, i.e. alpha, and the standard deviation of the stock price is replaced by the IVOL, i.e. the standard deviation of the residuals from the factor model.

4.3.1 Whole Sample (Jan 2002 - Sept 2014)

The annualized performance statistics from our whole sample tests are in Tables 4 and 5. The inclusion of cat bonds results in mean returns larger than our benchmark not including cat bonds, in all models except for Model 5, naive diversification. The volatility after including cat bonds is smaller in every case. This results in larger Sharpe ratios for all eight of our tests except in Model 5 where the Sharpe ratios are not statistically different from zero at the 5% level. The largest Sharpe ratio for our ILS test portfolio is 2.2314 but only 1.0136 for our benchmark portfolio. These differences are statistically significant at the 1% level. The smallest Sharpe ratio for our ILS test portfolio is 0.4438 for naive diversification (models 1 and 5) and 0.4527 for our benchmark portfolio, also naive diversification. Neither of these are statistically significant. The turnover for both portfolios is small, no higher than 1.6% in the worst case. We find lower turnover in every model indicating smaller implementation costs for ILS portfolios. However, the realized turnover would only marginally deteriorate the portfolios' performance even with the most aggressive of measures for market liquidity, for example 50 basis points [5]..

The risk-adjusted alphas for our ILS test portfolios are statistically significant at 5% and larger than the benchmark portfolios in every case, except for the naive model but the results are not statistically significant. The largest annualized alpha for the ILS portfolio is 5.64% compared to 3.27% for the benchmark portfolio. The smallest annualized alpha is 0.82% for the ILS portfolio and -0.26% for the benchmark portfolio. Given the superior risk adjusted expected returns of our ILS portfolios it is reasonable that information ratios are markedly larger in every case. The factor loadings also follow a similar pattern across both ILS and benchmark portfolios; that is the Fama-French factor loadings are rather small, < 0.5, while the bond market loadings are rather large, > 2.0. This pattern indicates a portfolio tilted towards exposure to bond market factors. The explanatory power of the factor model is also much smaller for our ILS portfolios indicating exposure to unknown sources of systematic risk. In summary, while the annualized mean returns are only marginally larger for our ILS portfolios, the ILS portfolios display much smaller standard

[5] This estimate was used in Kirby and Ostdiek (2012)

deviations and IVOL allowing for superior risk-adjusted performance.

In Figures 3, 4, and 5 we illustrate performance in terms of Sharpe ratios of portfolios when cat bonds are included and compare this to the performance of portfolios that do not contain cat bonds for each of the four asset allocation models. In the case of the naive diversification strategy, portfolios that contain cat bonds outperform those that do not in each of the 698 weeks in our sample. The models using Markowitz mean-variance, minimum variance, and volatility-timing strategies, portfolios that include cat bonds outperform portfolios that do not in roughly 80% of the weeks in our sample.

4.3.2 Market Tail Risk Performance

The weekly market tail performance statistics are found in Tables 7, 8, 10, and 10. Recall that we define **Bullish (Bearish)** markets as periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. Since the time periods are no longer consecutive for the market tail time periods, we do not report factor model statistics or turnovers for this analysis.

For the Bull markets the mean returns are approximately the same for both the ILS and benchmark models. However, as in the whole sample, the standard deviation is about half the size, resulting in superior risk-reward ratios. The largest risk-reward ratio is 1.0947 for the ILS portfolios and 1.0781 for the benchmark portfolios. The smallest risk-reward ratio is 0.5661 for the ILS portfolios and 0.2935 for the benchmark portfolio. Both portfolios have only 11 returns that are less than zero and neither sees returns less than minus five or minus ten percent.

Of interest is how the portfolio performance compares during the worst market conditions. Tables 10, and 10 show that the ILS portfolios are able to deliver positive reward-to-risk ratios even in the worst market conditions while the benchmark portfolio is negative in all models. We also show that for the best model for each portfolio, Model6 (Max-Sharpe ratio strategy), the ILS portfolios only have negative returns in 40 of the 197 time periods while the benchmark portfolio realize negative returns in 90 of 197 weeks. This compares to a reward-to-risk ratio of 0.2702 for ILS portfolios and −0.0924 for benchmark portfolios. This analysis illustrates cat bonds provide superior performance during times of market distress.

4.3.3 Portfolio Tail Risk Performance

Results for additional tail risk statistics for ILS portfolios are in Table 6. We compare the maximum drawdown, Calmar ratio, conditional value-at-risk (also known as the Expected Shortfall), and the frequency of large losses for both our benchmark and test portfolios. The maximum drawdown (MDD) is defined as the largest percentage drop in price from a peak to the subsequent bottom. It measures the worst-case scenario for an investor and is a popular risk metric in the mutual funds industry. An investor would earn this return if they invested and sold our candidate portfolios at the worst possible times. We find the ILS portfolio achieves a lower MDD in models 1 and 2 and a slightly larger MDD in models 3 and 4. The most favorable MDD for the benchmark portfolio is 5.56% compared to 5.37% for the ILS portfolio. The most unfavorable MDD is 13.50% for the benchmark portfolio compared to 16.45% for the ILS portfolio. The Calmar ratio is defined as the annualized rate of return divided by the MDD. This is also a popular mutual fund statistic and measures return versus downside risk. We find in every model the ILS portfolios have larger Calmar ratios than benchmark portfolios indicating higher return per unit of MDD. The largest Calmar ratio is 1.18 for ILS portfolios compared to 0.80 for benchmark portfolios while the smallest is 0.4325 compared to 0.4289 respectively. The conditional value-at-risk (Cvar) measures considered is more robust statistic than a simple value-at-risk measure. It is defined as the average of the worst q% of returns. We use $q = 5\%$ and find the ILS portfolios have a higher Cvar in all models. The best Cvar for ILS portfolios is -0.0069 compared to -0.0110 for benchmark portfolios. We also report the frequency of returns at levels of 0%, -5%, and -10%. ILS portfolios have the least number of negative and extreme returns for all optimization models with the exception of naive diversification where we find performance for the benchmark portfolios is marginally less than ILS portfolios. The fewest number of negative returns is 137 for ILS portfolios compared to 255 for benchmark portfolios while the most is 283 compared to 281 respectively.

4.3.4 NBER Date Recession Performance (Dec 2007 - June 2009)

Performance statistics during the NBER dated recession are in Tables 11 and 12. As expected, performance is worse for both portfolios across the board. While both portfolios yield negative mean returns, Sharpe ratios, and risk-adjusted alphas using naive diversification; the ILS portfolios statistics are better. The benchmark portfolio is unable to deliver positive raw or risk-adjusted returns in any of our models while for all optimization models except naive, the ILS portfolios yield positive measures. While many of these results are not significant at standard significant levels, we posit that this may be a function of the small sample size during the Recession period, i.e. 93 weeks. Perhaps the most striking evidence of the diversification benefits of cat bonds is found in Model 6, where the ILS portfolios realize the strongest performance. The ILS portfolios have an IR ratio of 1.4008 and a Sharpe ratio 0.3602 compared to the benchmark measures of −0.3095 and −0.7832. These results reinforce the conclusions from the Market Tail analysis that cat bonds provide substantial diversification benefits during poor market conditions.

Tail statistics[6] for the Recession are in Table 13. Every ILS portfolio statistic finds superior performance compared to the benchmark portfolio. In Model 6, the most favorable model, the ILS portfolio has a MDD of 3.33% and a Calmar ratio of 0.5835 compared to 5.40% and −.6643 for the benchmark portfolio. Consistent with the prior analyses the naive model provides the least favorable estimates for ILS portfolios. However, the ILS statistics are still more favorable than those from the benchmark portfolio.

4.4 Mean-Variance Spanning Tests

We estimate the mean-variance spanning test using a GMM Wald statistic under conditional heteroscedasticity. The results are reported in Table 14. All regimes show the ILS portfolios lie outside the mean-variance frontiers of the benchmark portfolios. The largest χ^2 statistic is 379.87 during Bull markets and the smallest χ^2 statistic is 35.27 during the Recession. Perhaps most convincing are the values of the estimates themselves; α is nearly zero during all regimes and the largest $\sum_{i=1}^{K} \beta_i$ is only 0.205. We posit the results illustrate a space of payoffs unattainable by holding benchmark assets alone.

5 Conclusion

In the alternative investments industry, catastrophe bonds are considered to bring diversification benefits to portfolios consisting of securities from other asset classes. In this paper, we have

[6] Note that we do report measures for the Cvar here because the Recession period is already much smaller than the whole sample (93 vs 688 weeks)

rigorously studied this claim. Our results shed additional light on the diversification potential of cat bonds.

Our analysis begins with an evaluation of the dynamic conditional correlations of cat bonds consistent with prior literature. GARCH-DCC model estimates indicate that cat bonds are relatively uncorrelated with major indices even during the recent financial crisis. The largest mean correlation during the recession is 0.1670 with the AGG index and only 0.1104 with the SPX index.

We further tested this pattern of low correlations in rigorous out-of-sample analyses to assess the benefits of diversification of cat bonds. We estimated portfolio using four portfolio models of varying levels of estimation risk; the largest hurdle to overcome in the portfolio literature. We use the Markowitz mean-variance model (the most estimation risk), the minimum variance model (2nd. most estimation risk), the volatility-timing model (Fleming et al., 2001; Fleming & Kirby, 2003), 3rd most estimation risk) and the naive $1/N$ model (Demiguel et al., 2009; Tu & Zhou, 2011), no estimation risk) for out-of-sample analysis. Our results indicate a pattern of marginally larger returns with significantly smaller standard deviations and idiosynchratic volatility. This pattern results in superior risk-adjusted statistics in nearly every case. Using traditional tail risk measures of maximum drawdown, Calmar ratio, and conditional value-at-risk, we find cat bonds add value by every measure.

Most importantly, when cat bond are added to the investor opportunity set, they improve out-of-sample performance during the poorest market conditions. In separate regimes containing both the extreme tails of the SXP market returns and the NBER date Recession, cat bonds have substantial benefits of diversification in all models.

Finally, we conduct mean-variance spanning tests under various market regimes. Our results indicate portfolios including cat bonds lie entirely outside the mean-variance frontier of our benchmark assets. cat bonds produce a space of payoffs completely unattainable by our benchmark assets. Thus, our results strongly support the existence of diversification benefits from adding cat bonds to portfolios of other securities.

6 Appendix

6.1 GARCH-DCC Estimation Methodology

Consider a return time series $r_t = \mu + \epsilon_t$, where μ is the expected return and ϵ_t is a zero-mean white noise. The GARCH model assumes a specific parametric form for the conditional heteroskedasticity. If $\epsilon_t = \sigma_t \eta_t$, where η_t is standard Gaussian ($\eta_t \sim$ IID N$(0,1)$), then;

$$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{12}$$

Where μ, ω, α, and β are parameters estimated by the GARCH(1,1) model by maximizing the conditional log-likelihood function, L_t. Following Bollerslev (1986), the log-likelihood and conditional log-likelihood functions of ϵ_t are given by

$$L_t = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\{-\frac{1}{2\sigma_t^2}\epsilon_t^2\} \tag{13}$$

$$L(\theta) = \frac{-1}{2}\sum_{t=1}^{T}(log2\pi + log\sigma_t^2(\theta + \frac{\epsilon_t^2(\theta)}{\sigma_t^2(\theta)})) \tag{14}$$

The assumption that η_t is Gaussian does not imply that the returns are Gaussian. Even though their conditional distribution is Gaussian, it is well known that that their conditional distribution presents excess kurtosis (fat tails).

For stationarity, $\alpha + \beta < 1$, the volatility exhibits mean reversion and fluctuates around σ, the square root of the unconditional variance. The unconditional variance is:

$$\sigma^2 = Var(r_t) = \frac{\omega}{1 - \alpha - \beta} \tag{15}$$

The restrictions on the parameters are ω, α, $\beta > 0$.

With the GARCH-DCC model, we consider n time series of returns and make the usual assumption that returns are serially uncorrelated. We then define a vector of zero-mean white noises, $\varepsilon_t = r_t - \mu$, where as in GARCH(1,1), r_t is the $n \times 1$ vector of returns and μ is the vector of expected returns. Although, returns are serially uncorrelated, they may present contemporaneous correlation. That is

$$\Sigma_t = E_{t-1}[(r_t - \mu)(r_t - \mu)'] \tag{16}$$

GARCH-DCC involves two steps. The first step accounts for the conditional heteroskedasticity and estimates each one of the n series of returns r_t^i and their conditional volatility σ_t^i using the GARCH model described above. We let D_t be a diagonal matrix with these conditional volatilities, i.e. $D_t^{i,i} = \sigma_t^i$ and if $i \neq j$, $D_t^{i,j} = 0$. Then the standardized residuals become

$$\nu_t = D_t^{-1}(r_t - \mu) \tag{17}$$

The standardized residuals have unit conditional volatility. Following Bollerslev (1990), we define matrix $\bar{R}$, which is the Bollerslev's Constant Conditional Correlation (CCC) Estimator.

$$\bar{R} = \frac{1}{T}\sum_{t=1}^{T} \nu_t \nu_t' \tag{18}$$

The second step of GARCH-DCC involve generalizing the Bollerslev's CCC to capture the dynamics in the correlation, hence the name Dynamic Conditional Correlation Correlation (DCC). The GARCH-DCC correlations are

$$Q_t = \bar{R} + \alpha(\nu_{t-1}\nu_{t-1}' - \bar{R}) + \beta(Q_{t-1} - \bar{R}) \tag{19}$$

Where $Q_t^{i,j}$ is the correlation between r_t^i and r_t^j at time t. In estimating the GARCH-DCC model, we first estimate standard GARCH for each of the n time series of returns. In the second step, we estimate both parameters α and β, simultaneously, by maximizing the log-likelihood function. The standard residuals are assumed to be jointly Gaussian. We let the parameters in D be denoted by θ and the additional parameters in R be denoted by ϕ. Following Engle (2002)), the log-likelihood can be written as the sum of the volatility part and the correlation part

$$L(\theta, \phi) = L_V(\theta) + L_C(\theta, \phi) \tag{20}$$

The volatility term is

$$L_V(\theta) = -\frac{1}{2}\Sigma_t(nlog(2\pi) + log|D_t|^2 + r_t' D_t^{-1} r_t) \tag{21}$$

and the correlation component is

$$L_C(\theta, \phi) = -\frac{1}{2}\Sigma_t(log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t) \tag{22}$$

The DCC model captures the correlation clustering stylized fact in financial time series. The correlation is more likely to be high at time t if it was also high at time $t-1$. Another way of seeing this is noting that a shock at time $t-1$ also impacts the correlation at time t.

6.2 Asset Allocation Models

6.2.1 Markowitz Mean-Variance

In general the Markowitz Mean-Variance model is computed such at each time, t, the investor chooses a portfolio, w_t to minimize portfolio variance as follows:

$$\min_{w_t} w_t'\Sigma_t w_t \qquad \text{subject to} \qquad \mathrm{E}[r_p] = w_t'\mu = \bar{\mu}_t \quad \text{and} \qquad \mathrm{w}_t' e = 1 \tag{23}$$

where r_p is the $N \times 1$ vector of the portfolio returns, e is an $N \times 1$ vector of ones, and $\bar{\mu}$ is the desired expected return for the portfolio. The solution to (1) is:

$$w^* = \frac{\bar{\mu}_t}{\mu_t'\Sigma_t^{-1}\mu_t}\Sigma_t^{-1}\bar{\mu} \tag{24}$$

We also refer to this model as the Max Sharpe Ratio model. Since we impose short-sale constraints the Lagrangian to the maximization problem is:

$$\ell = w_t'\mu_t - \frac{\lambda}{2} w_t'\Sigma_t w_t + w_t'\zeta_t \tag{25}$$

Where ζ_t is an $N \times 1$ vector of Lagrange multiplier on short-selling. Comparing Equations 24 and 25, we can see that the constrained mean-variance portfolio weights are equivalent to the unconstrained weights with the difference coming from the adjusted mean vector; $\tilde{\mu}_t = \mu_t + \zeta_t$.

6.2.2 Minimum-Variance

Under the general minimum-variance strategy, we choose the portfolio of risky assets that minimizes the variance of returns assuming that all the weights sum to one (investing all our wealth).

$$\min_{w_t} w_t' \Sigma_t w_t \qquad \text{subject to} \quad w_t' e = 1 \tag{26}$$

The solution to (7) is:

$$w_{minvar}^{*} = \frac{1}{e' \Sigma_t^{-1} e} \Sigma_t^{-1} e \tag{27}$$

Equation 27 is the "global minimum variance portfolio" of risky assets that has minimum variance among all portfolios of risky assets. To implement this strategy, we use the estimate of the covariance matrix of asset returns. That is, we use the sample covariance matrix and completely ignore the estimates of the expected returns. As with the Max-Sharpe ratio strategy we impose short-selling constraints and our Lagrangian to the maximization problem becomes:

$$\ell = \frac{1}{2} w_t' \Sigma_t w_t + w_t' \zeta_t \tag{28}$$

With minimum-variance with short constraints, Jagannathan and Ma (2003) show that imposing a short-sale constraint on the minimum-variance portfolio shrinks the largest eigenvalues in the system thus reducing estimation risk. Jagannathan and Ma (2003) find that minimum variance with constraints performs best in terms of Sharpe ratios and this finding supports our inclusion of this model in our analysis.

6.2.3 Volatility Timing

Fleming et al. (2001); Fleming and Kirby (2003) introduced a class of active portfolio strategies, referred to as "volatility-timing," where the weights are function of the estimated conditional covariance matrix of returns. Kirby and Ostdiek (2012) alter these volatility-timing strategies to combine some of the most attractive features of naive diversification. Specifically they restrict the covariance matrix of excess returns to be diagonal such that the weights are given as:

$$\hat{w}_{it} = \frac{(1/\hat{\sigma}_{it}^2)}{\sum_{1=1}^{N}(1/\hat{\sigma}_{it}^2)} \tag{29}$$

In this specification $\hat{\sigma}_{it}^2$ is just the estimated conditional volatility for the ith risky asset. They refer to this as an aggressive form of shrinkage in the spirit of Ledoit and Wolf (2004). The principle idea is that there are now $N(N-1)/2$ fewer parameters to estimate thus greatly reducing estimation error. Furthermore, as with naive diversification, this model involves no optimization, no matrix inversion, and no shorts. These models perform exceptionally well in the Kirby and Ostdiek (2012) study and represents a newer class of portfolio optimization models the aforementioned strategies.

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Table 1: Catastrophe bonds and ILS risk capital outstanding by risk or peril

Type	Percentage of Outstanding Capital (%)
U.S. multi-peril	25.4
International multi-peril	22.6
U.S. named storm and hurricane	20.7
U.S. earthquake	7.9
European windstorm	7.4
Japan earthquake	6.1
Extreme mortality	3.8
Healthcare	2.0
Turkey earthquake	1.6
Japan typhoon	0.9
Storm surge	0.8
Lottery winning risk	0.3
Longevity	0.2
Caribbean multi-peril	0.1

Figure 1: Catastrophe Bond & ILS Risk Capital Issued and Outstanding by Year, in Millions

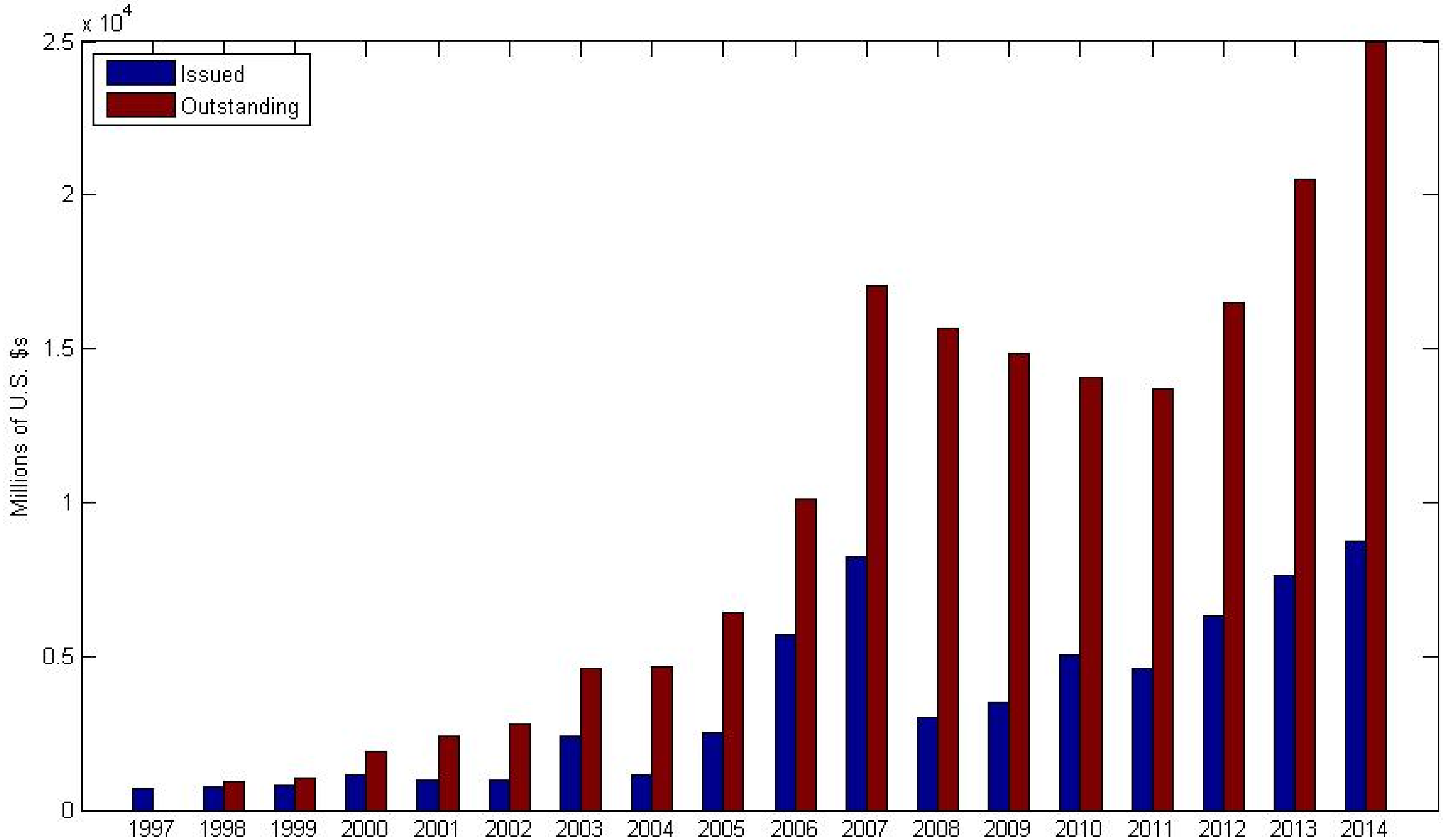

Figure 2: Dynamic Conditional Correlation of SRG with other Asset Classes

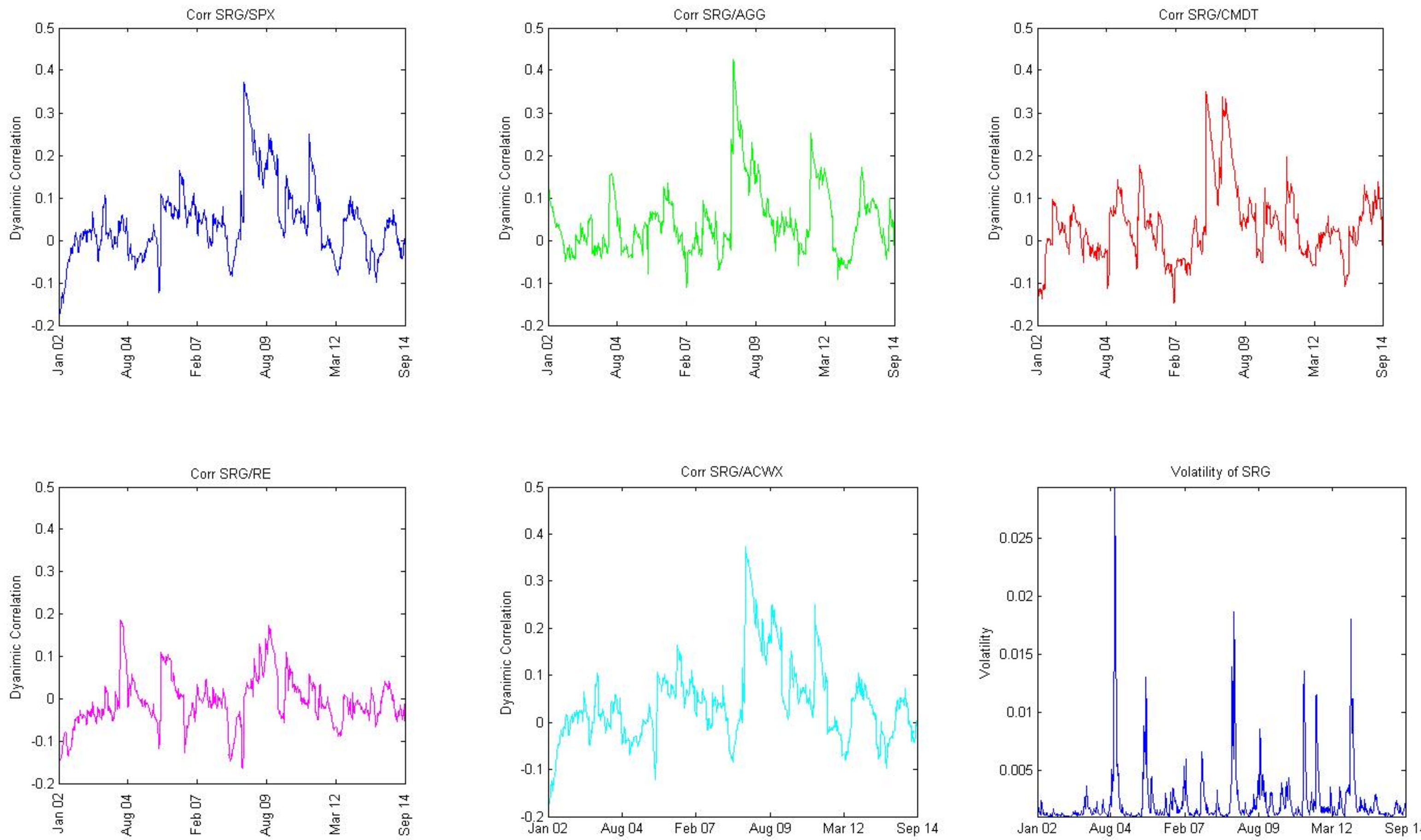

Table 2: Summary statistics for the 6 indices used in our analysis for the whole sample (Jan 2002 - Sept 2014) and an NBER dated recession (Dec 2007 - June 2009).

Stats	Srg	Spx	Agg	Cmdt	Re	Acwx
Whole Sample						
Ann Mean	0.0714	0.0552	0.0433	0.0735	0.0832	0.0642
Ann Stdev	0.0237	0.1692	0.0343	0.1845	0.2500	0.1879
Ann Median	0.0687	0.1036	0.0487	0.1581	0.1925	0.1618
Ann RRratio	3.0161	0.3263	1.2618	0.3984	0.3328	0.3420
And SharpeR	2.4898	0.2527	0.8985	0.3309	0.2830	0.2757
Skewness	-1.6064	-0.8160	-0.4186	-0.9830	-0.4444	-1.4665
Kurtosis	46.2974	12.1856	4.2727	7.3431	11.4879	15.4299
MaxDD	0.0591	0.2542	0.0345	0.2181	0.3153	0.2810
Calmar Ratio	1.2073	0.2172	1.2542	0.3371	0.2638	0.2286
Prob SR>0	0.0000	0.2251	0.0000	0.1418	0.2124	0.2112
Recession						
Ann Mean	0.0368	-0.2448	0.0407	-0.1528	-0.3697	-0.2750
Ann Stdev	0.0273	0.3037	0.0481	0.3074	0.5161	0.3512
Ann Median	0.0614	-0.1164	0.0614	-0.0447	-0.0730	-0.0407
Ann RRratio	1.3468	-0.8060	0.8459	-0.4970	-0.7163	-0.7829
And SharpeR	0.9535	-0.8414	0.6223	-0.5320	-0.7371	-0.8135
Skewness	-4.4877	-0.6412	-0.4758	-0.7964	-0.0466	-1.1844
Kurtosis	29.5349	7.5237	3.5869	4.6630	4.3789	8.3186
MaxDD	0.0341	0.2327	0.0313	0.2145	0.3153	0.2810
Calmar Ratio	1.0793	-1.0520	1.2987	-0.7122	-1.1725	-0.9784
Prob SR>0	0.2108	0.2658	0.2704	0.4928	0.3364	0.2652

Table 3: Summary statistics for the 6 indices used in our analysis for Bull(Top 30% of return weeks for SPX) and Bear Markets(Bot 30% of return weeks for SPX).

Stats	Srg	Spx	Agg	Cmdt	Re	Acwx
Bull Markets						
Ann Mean	0.0872	1.2642	-0.0383	0.3884	1.2433	1.0753
Ann Stdev	0.0211	0.1135	0.0347	0.1838	0.2478	0.1380
Ann Median	0.0799	0.9684	-0.0344	0.4070	1.1013	0.9823
Ann RRratio	4.1222	11.1370	-1.1023	2.1137	5.0166	7.7915
And SharpeR	3.4990	11.0209	-1.4819	2.0419	4.9634	7.6960
Skewness	-0.8569	2.6471	-0.1295	-0.8536	1.2376	1.2114
Kurtosis	14.8259	12.1639	3.0126	6.2879	11.9150	7.1633
MaxDD	0.0285	0.0922	0.0249	0.1571	0.2772	0.1356
Calmar Ratio	3.0541	13.7139	-1.5398	2.4719	4.4857	7.9300
Prob SR>0	0.0000	0.0000	0.0214	0.0002	0.0000	0.0000
Bear Markets						
Ann Mean	0.0684	-1.2286	0.1173	-0.3016	-1.2099	-1.1004
Ann Stdev	0.0215	0.1442	0.0367	0.2168	0.2562	0.1986
Ann Median	0.0634	-0.9528	0.1457	-0.1013	-0.7620	-0.8916
Ann RRratio	3.1770	-8.5203	3.1964	-1.3913	-4.7217	-5.5417
And SharpeR	2.6057	-8.6056	2.8614	-1.4480	-4.7697	-5.6037
Skewness	-4.3951	-3.7929	-1.0266	-1.3148	-2.0765	-2.9898
Kurtosis	36.1426	29.2618	5.9443	7.1305	9.5498	21.7372
MaxDD	0.0342	0.1953	0.0348	0.2145	0.2253	0.2810
Calmar Ratio	2.0024	-6.2918	3.3756	-1.4060	-5.3696	-3.9154
Prob SR>0	0.0021	0.0000	0.0000	0.0012	0.0000	0.0000

NOTE: 18.14% of the Bear Market days fell in the NBER Recession period (Dec 2007 - June 2009) and 12.50% of the Bull Market days fell in the NBER Recession period (Dec 2007 - June 2009)

Table 4: **WHOLE SAMPLE APPROACH 1:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer.

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
Ann Mean	0.0706	0.0707	0.0473	0.0633	0.0457	0.0606	0.0460	0.0607
Ann Stdev	0.1287	0.1080	0.0400	0.0229	0.0329	0.0230	0.0350	0.0227
Ann Median	0.1375	0.1097	0.0598	0.0657	0.0590	0.0689	0.0579	0.0640
Ann SharpeR	0.4527	0.5406	0.8737	2.2314	1.0136	2.0999	0.9641	2.1360
Skewness	-0.9574	-1.0088	-0.9678	-2.4677	-1.4675	-2.7181	-1.3203	-2.4683
Kurtosis	12.6551	13.1479	8.8453	33.8053	15.9633	38.5381	15.4932	40.5267
Turnover	0.0159	0.0136	0.0135	0.0088	0.0096	0.0074	0.0062	0.0051
Prob SR>0	0.9441	0.9758	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000
P_{val} SR_{ILS}>SR_b	1.0000	0.0000	1.0000	0.0022	1.0000	0.0028	1.0000	0.0051
Ann Alpha	-0.0026	0.0082	0.0320	0.0551	0.0327	0.0494	0.0309	0.0506
tstat	-0.1418	0.5189	3.4542	7.6275	7.1781	7.9526	5.8664	7.5526
BetaMkt	0.6669	0.5599	0.1301	0.0484	0.1330	0.0795	0.1449	0.0634
tstat	43.0627	42.8626	16.9162	8.0615	35.1452	15.3875	33.1317	11.3824
BetaSMB	0.0381	0.0255	0.0175	-0.0262	-0.0162	-0.0260	-0.0058	-0.0280
tstat	1.3106	1.0428	1.2139	-2.3306	-2.2749	-2.6782	-0.7095	-2.6803
BetaHML	0.1569	0.1326	0.0326	0.0096	0.0018	0.0094	0.0166	0.0090
tstat	5.4323	5.4423	2.2734	0.8581	0.2550	0.9742	2.0297	0.8645
BetaMOM	-0.0017	-0.0002	0.0320	0.0155	0.0005	0.0033	-0.0055	0.0016
tstat	-0.1063	-0.0171	4.1250	2.5523	0.1356	0.6411	-1.2385	0.2828
BetaBondP1	4.3112	3.6503	9.4093	2.3967	9.9191	3.6957	9.9194	2.9667
tstat	4.9816	5.0003	21.8999	7.1423	46.8932	12.7993	40.5739	9.5238
BetaBondP2	1.6859	1.5363	6.3463	2.1255	6.0131	2.7159	6.0790	2.3099
tstat	2.1677	2.3417	16.4364	7.0483	31.6327	10.4663	27.6688	8.2512
BetaBondP3	-0.9941	-0.8781	1.3367	0.1735	1.3401	0.4878	1.2478	0.3796
tstat	-1.2468	-1.3056	3.3770	0.5611	6.8767	1.8338	5.5401)	1.3227
R2	0.8251	0.8231	0.5543	0.1674	0.8401	0.3900	0.8108	0.2690
IRalpha	-0.0491	0.1796	1.1952	2.6392	2.4837	2.7517	2.0298	2.6133

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M4: Volatility Timing, See Kirby and Ostdiek (2012)

Table 5: **WHOLE SAMPLE APPROACH 2:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio was constructed as an equally weighted portfolio of five portfolios. The five portfolios included all combinations of the indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR), each one excluding one of the non cat Bond indices. Refer to the text for more details. The portfolio strategy for each model is defined in the footer.

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
Ann Mean	0.0706	0.0584	0.0473	0.0526	0.0457	0.0501	0.0460	0.0503
Ann Stdev	0.1287	0.1039	0.0400	0.0231	0.0329	0.0228	0.0350	0.0228
Ann Median	0.1375	0.1017	0.0598	0.0576	0.0590	0.0581	0.0579	0.0508
Ann SharpeR	0.4527	0.4438	0.8737	1.7441	1.0136	1.6602	0.9641	1.6716
Skewness	-0.9574	-1.0032	-0.9678	-2.4707	-1.4675	-2.6935	-1.3203	-2.3840
Kurtosis	12.6551	13.2485	8.8453	35.8050	15.9633	40.7427	15.4932	42.1768
Turnover	0.0159	0.0131	0.0135	0.0079	0.0096	0.0076	0.0062	0.0046
Prob SR>0	0.9441	0.8887	0.9999	0.9969	1.0000	0.9989	1.0000	0.9983
P_{val} $SR_{ILS}>SR_b$	1.0000	0.0000	1.0000	0.0026	1.0000	0.0039	1.0000	0.0054
Ann Alpha	-0.0026	0.0103	0.0320	0.0564	0.0327	0.0513	0.0309	0.0524
tstat	-0.1418	0.6808	3.4542	7.6112	7.1781	7.8136	5.8664	7.5445
BetaMkt	0.6669	0.5385	0.1301	0.0467	0.1330	0.0715	0.1449	0.0594
tstat	43.0627	42.7624	16.9162	7.5907	35.1452	13.1107	33.1317	10.2827
BetaSMB	0.0381	0.0230	0.0175	-0.0287	-0.0162	-0.0288	-0.0058	-0.0297
tstat	1.3106	0.9756	1.2139	-2.4884	-2.2749	-2.8105	-0.7095	-2.7376
BetaHML	0.1569	0.1277	0.0326	0.0102	0.0018	0.0097	0.0166	0.0099
tstat	5.4323	5.4382	2.2734	0.8924	0.2550	0.9580	2.0297	0.9211
BetaMOM	-0.0017	0.0001	0.0320	0.0154	0.0005	0.0045	-0.0055	0.0028
tstat	-0.1063	0.0049	4.1250	2.4763	0.1356	0.8106	-1.2385	0.4766
BetaBondP1	4.3112	3.5181	9.4093	2.0039	9.9191	2.9669	9.9194	2.4748
tstat	4.9816	4.9990	21.8999	5.8262	46.8932	9.7282	40.5739	7.6658
BetaBondP2	1.6859	1.5063	6.3463	1.9039	6.0131	2.3697	6.0790	2.0298
tstat	2.1677	2.3817	16.4364	6.1593	31.6327	8.6460	27.6688	6.9961
BetaBondP3	-0.9941	-0.8549	1.3367	0.1108	1.3401	0.3646	1.2478	0.2518
tstat	-1.2468	-1.3185	3.3770	0.3496	6.8767	1.2976	5.5401	0.8467
R2	0.8251	0.8223	0.5543	0.1412	0.8401	0.3066	0.8108	0.2206
IRalpha	-0.0491	0.2356	1.1952	2.6335	2.4837	2.7036	2.0298	2.6105

M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 6: **WHOLE SAMPLE TAIL STATISTICS:** Tail statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio was constructed as an equally weighted portfolio of five portfolios. The five portfolios included all combinations of the indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR), each one excluding one of the non cat Bond indices. Refer to the text for more details. The portfolio strategy for each model is defined in the footer. The statistics include the Maximum Drawdown, Calmar Ratio, Conditional Value at Risk (5% level, also known as the Expected Shortfall), number of out of sample returns, the number of returns less than zero, -5%, and -10%.

Approach 1

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
MaxDD	0.1645	0.1401	0.0590	0.0537	0.0556	0.0590	0.0577	0.0585
Calmar	0.4289	0.5044	0.8012	1.1793	0.8208	1.0270	0.7971	1.0374
Cvar	-0.0459	-0.0382	-0.0129	-0.0072	-0.0103	-0.0070	-0.0110	-0.0069
N	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000
R<0%	281.0000	278.0000	265.0000	137.0000	255.0000	164.0000	260.0000	147.0000
R<-5%	9.0000	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Approach 2

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
MaxDD	0.1645	0.1350	0.0590	0.0552	0.0556	0.0597	0.0577	0.0592
Calmar	0.4289	0.4325	0.8012	0.9522	0.8208	0.8393	0.7971	0.8496
Cvar	-0.0459	-0.0368	-0.0129	-0.0075	-0.0103	-0.0072	-0.0110	-0.0072
N	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000	688.0000
R<0%	281.0000	283.0000	265.0000	154.0000	255.0000	170.0000	260.0000	149.0000
R<-5%	9.0000	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)
M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)
M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)
M4: Volatility Timing, See Kirby and Ostdiek (2012)
M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)
M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)
M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)
M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 7: **BULL MARKETS APPROACH 1:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. **Bullish (bearish)** markets are defined as the periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. **Note** that the Turnover statistic is meaningless in these regime scenarios since periods are no longer adjacent in time.

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
Mean	0.0153	0.0130	0.0017	0.0016	0.0018	0.0020	0.0021	0.0018
Stdev	0.0142	0.0119	0.0058	0.0029	0.0045	0.0028	0.0048	0.0027
Median	0.0123	0.0105	0.0020	0.0016	0.0019	0.0021	0.0021	0.0018
RRratio	1.0781	1.0947	0.2935	0.5661	0.4012	0.7371	0.4387	0.6669
Skewness	2.2306	2.1953	-0.2765	-0.6891	0.0508	-0.4743	0.3135	-0.4821
Kurtosis	11.8627	11.6862	4.9922	9.0968	4.1250	6.9454	5.0208	8.0482
Turnover	–	–	–	–	–	–	–	–
Prob SR>0	1.0000	1.0000	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000
P_{val} SR_{ILS}>SR_b	0.0002	0.0002	0.0141	0.0141	0.0005	0.0005	0.0447	0.0447
N	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000
R< 0%	11.0000	11.0000	82.0000	43.0000	66.0000	40.0000	65.0000	41.0000
R<-5%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M4: Volatility Timing, See Kirby and Ostdiek (2012)

Table 8: **BULL MARKETS APPROACH 2:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. **Bullish (bearish)** markets are defined as the periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. **Note** that the Turnover statistic is meaningless in these regime scenarios since periods are no longer adjacent in time.

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
Mean	0.0153	0.0126	0.0017	0.0017	0.0018	0.0020	0.0021	0.0018
Stdev	0.0142	0.0115	0.0058	0.0029	0.0045	0.0027	0.0048	0.0027
Median	0.0123	0.0102	0.0020	0.0016	0.0019	0.0021	0.0021	0.0018
RRratio	1.0781	1.0985	0.2935	0.5913	0.4012	0.7448	0.4387	0.6847
Skewness	2.2306	2.1850	-0.2765	-0.7645	0.0508	-0.6426	0.3135	-0.5967
Kurtosis	11.8627	11.6330	4.9922	10.1770	4.1250	8.8080	5.0208	9.4788
Turnover	–	–	–	–	–	–	–	–
Prob SR>0	1.0000	1.0000	0.9999	1.0000	1.0000	1.0000	1.0000	1.0000
P_{val} $SR_{ILS}>SR_b$	0.0002	0.0002	0.0140	0.0140	0.0037	0.0037	0.0579	0.0579
N	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000	207.0000
R<0%	11.0000	11.0000	82.0000	41.0000	66.0000	36.0000	65.0000	35.0000
R<-5%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 9: **BEAR MARKETS APPROACH 1:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. **Bullish (bearish)** markets are defined as the periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. **Note** that the Turnover statistic is meaningless in these regime scenarios since periods are no longer adjacent in time.

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
Mean	-0.0151	-0.0124	-0.0006	0.0009	-0.0006	0.0002	-0.0009	0.0005
Stdev	0.0186	0.0157	0.0062	0.0033	0.0053	0.0036	0.0056	0.0033
Median	-0.0101	-0.0082	0.0004	0.0012	0.0004	0.0007	-0.0001	0.0010
RRratio	-0.8142	-0.7905	-0.0924	0.2669	-0.1054	0.0584	-0.1665	0.1566
Skewness	-2.5870	-2.6732	-1.8550	-4.4236	-2.9925	-5.4281	-2.7926	-5.1323
Kurtosis	13.3151	14.1816	11.7826	37.0407	22.7023	52.6926	20.7423	48.0332
Turnover	–	–	–	–	–	–	–	–
Prob SR>0	1.0000	1.0000	0.8413	0.9745	0.9143	0.5185	0.9958	0.8721
$P_{val}\ SR_{ILS}>SR_b$	0.0000	0.0000	0.0013	0.0013	0.0201	0.0201	0.0011	0.0011
N	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000
R<0%	171.0000	170.0000	90.0000	43.0000	94.0000	67.0000	101.0000	56.0000
R<-5%	9.0000	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M4: Volatility Timing, See Kirby and Ostdiek (2012)

Table 10: **BEAR MARKETS APPROACH 2:** Statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. **Bullish (bearish)** markets are defined as the periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period. **Note** that the Turnover statistic is meaningless in these regime scenarios since periods are no longer adjacent in time.

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
Mean	-0.0151	-0.0118	-0.0006	0.0009	-0.0006	0.0003	-0.0009	0.0006
Stdev	0.0186	0.0151	0.0062	0.0033	0.0053	0.0035	0.0056	0.0033
Median	-0.0101	-0.0079	0.0004	0.0011	0.0004	0.0008	-0.0001	0.0009
RRratio	-0.8142	-0.7846	-0.0924	0.2702	-0.1054	0.0978	-0.1665	0.1780
Skewness	-2.5870	-2.6946	-1.8550	-4.6170	-2.9925	-5.5871	-2.7926	-5.2225
Kurtosis	13.3151	14.4034	11.7826	38.8632	22.7023	53.9764	20.7423	48.4579
Turnover	–	–	–	–	–	–	–	–
Prob SR>0	1.0000	1.0000	0.8413	0.9733	0.9143	0.7123	0.9958	0.9006
P_{val} $SR_{ILS}>SR_b$	0.0000	0.0000	0.0021	0.0021	0.0176	0.0176	0.0015	0.0015
N	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000	197.0000
R<0%	171.0000	170.0000	90.0000	40.0000	94.0000	62.0000	101.0000	54.0000
R<-5%	9.0000	6.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 11: **RECESSION APPROACH 1:** Statistics for out of sample returns during a recession period as defined by the NBER for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. The recession period is defined by the NBER and consists of all weeks within the dates of Dec 2007 - June 2009.

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
Ann Mean	-0.2003	-0.1608	-0.0359	0.0194	0.0000	0.0122	-0.0101	0.0198
Ann Stdev	0.2450	0.2057	0.0595	0.0296	0.0534	0.0363	0.0589	0.0332
Ann Median	-0.0268	-0.0142	0.0130	0.0532	0.0348	0.0359	0.0246	0.0446
Ann SharpeR	-0.8616	-0.8341	-0.7832	0.2934	-0.2005	0.0392	-0.3541	0.2715
Skewness	-0.4262	-0.4811	-1.4247	-4.4332	-1.9122	-4.0128	-1.4766	-4.0214
Kurtosis	5.8334	6.0596	8.5049	29.9089	14.0546	29.0518	11.8151	28.2802
Turnover	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob SR>0	0.7611	0.7470	0.7407	0.2803	0.2173	0.0414	0.3766	0.2641
P_{val} $SR_{ILS}>SR_b$	0.1729	0.1729	0.1911	0.1911	0.7854	0.7854	0.3493	0.3493
Ann Alpha	-0.1266	-0.1000	-0.0130	0.0298	0.0278	0.0252	0.0176	0.0275
tstat	-1.2693	-1.1857	-0.2508	1.1123	0.9193	0.9591	0.5239	1.0858
BetaMkt	0.7617	0.6438	0.1535	0.0747	0.1421	0.1080	0.1631	0.0929
tstat	16.4190	16.4104	6.3585	5.9927	10.0958	8.8501	10.4426	7.8976
BetaSMB	0.1795	0.1366	0.0065	-0.0617	-0.0431	-0.0547	-0.0213	-0.0565
tstat	1.9741	1.7773	0.1379	-2.5274	-1.5625	-2.2886	-0.6969	-2.4516
BetaHML	-0.0112	-0.0163	-0.0826	-0.0501	-0.0618	-0.0504	-0.0595	-0.0490
tstat	-0.1193	-0.2052	-1.6875	-1.9841	-2.1649	-2.0382	-1.8791	-2.0534
BetaMOM	0.0052	0.0052	0.0024	0.0075	-0.0186	-0.0026	-0.0251	-0.0056
tstat	0.1012	0.1211	0.0893	0.5484	-1.2040	-0.1955	-1.4609	-0.4334
BetaBondP1	1.8386	1.7775	8.0115	3.3933	9.4632	4.5537	9.3661	4.2755
tstat	0.7435	0.8501	6.2270	5.1076	12.6137	6.9987	11.2487	6.8158
BetaBondP2	-2.7683	-2.1245	4.6860	2.2805	5.6619	2.7644	5.2583	2.5779
tstat	-1.3440	-1.2198	4.3729	4.1214	9.0611	5.1011	7.5823	4.9341
BetaBondP3	-3.0776	-2.6535	0.7162	-0.0922	1.3886	0.1837	0.9605	0.0011
tstat	-1.6000	-1.6315	0.7157	-0.1783	2.3797	0.3630	1.4832	0.0023
R2	0.8911	0.8895	0.5010	0.4606	0.7890	0.6566	0.7866	0.6185
IRalpha	-1.5662	-1.4630	-0.3095	1.3725	1.1344	1.1834	0.6465	1.3398

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M4: Volatility Timing, See Kirby and Ostdiek (2012)

Table 12: **RECESSION APPROACH 2:** Statistics for out of sample returns during a recession period as defined by the NBER for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio included all of indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR). The portfolio strategy for each model is defined in the footer. The recession period is defined by the NBER and consists of all weeks within the dates of Dec 2007 - June 2009.

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
Ann Mean	-0.2003	-0.1529	-0.0359	0.0213	0.0000	0.0143	-0.0101	0.0214
Ann Stdev	0.2450	0.1978	0.0595	0.0292	0.0534	0.0343	0.0589	0.0320
Ann Median	-0.0268	-0.0080	0.0130	0.0531	0.0348	0.0397	0.0246	0.0461
Ann SharpeR	-0.8616	-0.8272	-0.7832	0.3602	-0.2005	0.1042	-0.3541	0.3330
Skewness	-0.4262	-0.4952	-1.4247	-4.7073	-1.9122	-4.4332	-1.4766	-4.3276
Kurtosis	5.8334	6.1189	8.5049	32.2449	14.0546	32.1724	11.8151	30.3996
Turnover	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Prob SR>0	0.7611	0.7434	0.7407	0.3324	0.2173	0.1075	0.3766	0.3140
P_{val} $SR_{ILS}>SR_b$	0.1723	0.1723	0.2087	0.2087	0.7620	0.7620	0.3823	0.3823
Ann Alpha	-0.1266	-0.0947	-0.0130	0.0306	0.0278	0.0256	0.0176	0.0276
tstat	-1.2693	-1.1646	-0.2508	1.1353	0.9193	0.9762	0.5239	1.0789
BetaMkt	0.7617	0.6202	0.1535	0.0739	0.1421	0.1013	0.1631	0.0897
tstat	16.4190	16.4008	6.3585	5.8995	10.0958	8.3164	10.4426	7.5296
BetaSMB	0.1795	0.1281	0.0065	-0.0667	-0.0431	-0.0591	-0.0213	-0.0595
tstat	1.9741	1.7282	0.1379	-2.7179	-1.5625	-2.4745	-0.6969	-2.5480
BetaHML	-0.0112	-0.0173	-0.0826	-0.0492	-0.0618	-0.0493	-0.0595	-0.0478
tstat	-0.1193	-0.2262	-1.6875	-1.9390	-2.1649	-1.9979	-1.8791	-1.9816
BetaMOM	0.0052	0.0052	0.0024	0.0084	-0.0186	-0.0005	-0.0251	-0.0031
tstat	0.1012	0.1260	0.0893	0.6100	-1.2040	-0.0357	-1.4609	-0.2369
BetaBondP1	1.8386	1.7653	8.0115	3.0172	9.4632	3.9100	9.3661	3.7406
tstat	0.7435	0.8758	6.2270	4.5185	12.6137	6.0225	11.2487	5.8914
BetaBondP2	-2.7683	-1.9957	4.6860	2.0745	5.6619	2.4700	5.2583	2.2750
tstat	-1.3440	-1.1888	4.3729	3.7300	9.0611	4.5678	7.5823	4.3020
BetaBondP3	-3.0776	-2.5687	0.7162	-0.1449	1.3886	0.0754	0.9605	-0.1152
tstat	-1.6000	-1.6385	0.7157	-0.2789	2.3797	0.1494	1.4832	-0.2333
R2	0.8911	0.8891	0.5010	0.4423	0.7890	0.6175	0.7866	0.5803
IRalpha	-1.5662	-1.4370	-0.3095	1.4008	1.1344	1.2045	0.6465	1.3313

M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)

M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)

M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)

M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 13: **RECESSION TAIL STATISTICS:** Tail statistics for out of sample returns for a benchmark portfolio vs. test portfolio including the ILS cat bonds. The benchmark portfolio included the weekly indices for the Standard and Poor's 500 Index (SPX), MSCI ACWI ex US Index (ACWX), Barclay's Agg (AGG), Deutsche Bank Liquid Commodity Index (DBLCI), and the Dow Jones Real Estate Index (DJRE). The test portfolio was constructed as an equally weighted portfolio of five portfolios. The five portfolios included all combinations of the indices from the benchmark portfolio plus the SwissRe Global Cat Bond Total Return Index (SRGLTRR), each one excluding one of the non cat Bond indices. Refer to the text for more details. The portfolio strategy for each model is defined in the footer. The statistics include the Maximum Drawdown, Calmar Ratio, Conditional Value at Risk (5% level, also known as the Expected Shortfall), number of out of sample returns, the number of returns less than zero, -5%, and -10%. The recession period is defined by the NBER and consists of all weeks within the dates of Dec 2007 - June 2009.

Approach 1

Stats	M1bench	M1ILS	M2bench	M2ILS	M3bench	M3ILS	M4bench	M4ILS
MaxDD	0.1645	0.1401	0.0540	0.0333	0.0523	0.0403	0.0549	0.0362
Calmar	-1.2175	-1.1478	-0.6643	0.5835	0.0008	0.3017	-0.1842	0.5453
N	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000
R<0%	48.0000	48.0000	44.0000	28.0000	40.0000	33.0000	42.0000	30.0000
R<-5%	6.0000	4.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Approach 2

Stats	M5bench	M5ILS	M6bench	M6ILS	M7bench	M7ILS	M8bench	M8ILS
MaxDD	0.1645	0.1351	0.0540	0.0339	0.0523	0.0385	0.0549	0.0352
Calmar	-1.2175	-1.1315	-0.6643	0.6273	0.0008	0.3725	-0.1842	0.6078
N	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000	93.0000
R<0%	48.0000	48.0000	44.0000	26.0000	40.0000	31.0000	42.0000	29.0000
R<-5%	6.0000	4.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R<-10%	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

M1: naive diversification, i.e. 1/N, See Demiguel et al. (2009)
M2: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)
M3: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)
M4: Volatility Timing, See Kirby and Ostdiek (2012)
M5: naive diversification, i.e. 1/N, See Demiguel et al. (2009)
M6: MaxSharpe ratio, i.e. the tangency portfolio, See Demiguel et al. (2009)
M7: Minimum variance portfolio i.e., global minimum portfolio, See Jagannathan and Ma (2003)
M8: Volatility Timing, See Kirby and Ostdiek (2012)

Table 14: **MEAN VARIANCE SPANNING TESTS:** Test statistics for mean variance spanning tests using 1) the whole sample, 2) bull markets, 3) bear markets, and 4) recession period. The recession period is defined by the NBER and consists of all weeks within the dates of Dec 2007 - June 2009. **Bullish (bearish)** markets are defined as the periods when the market index (SPX) returns are among the top (bottom) 30% of the whole sample period.

Stats	Whole Sample	Bull Markets	Bear Markets	Recessions
Alpha	0.0013	0.0018	0.0025	0.0007
BetaSPX	0.0094	-0.0558	0.0709	0.0473
BetaAGG	0.0740	0.0114	0.1042	0.1570
BetaCMDT	0.0074	-0.0002	0.0096	0.0181
BetaRE	-0.0045	0.0145	-0.0194	-0.0196
BetaACWX	0.0145	0.0431	0.0048	0.0022
SumBeta	0.1008	0.0129	0.1701	0.2050
Chi2stat	125.9078	379.8736	251.1726	35.2654
Waldp	0.0000	0.0000	0.0000	0.0000

Figure 3: Rolling Sharpe Ratios for naive Diversification

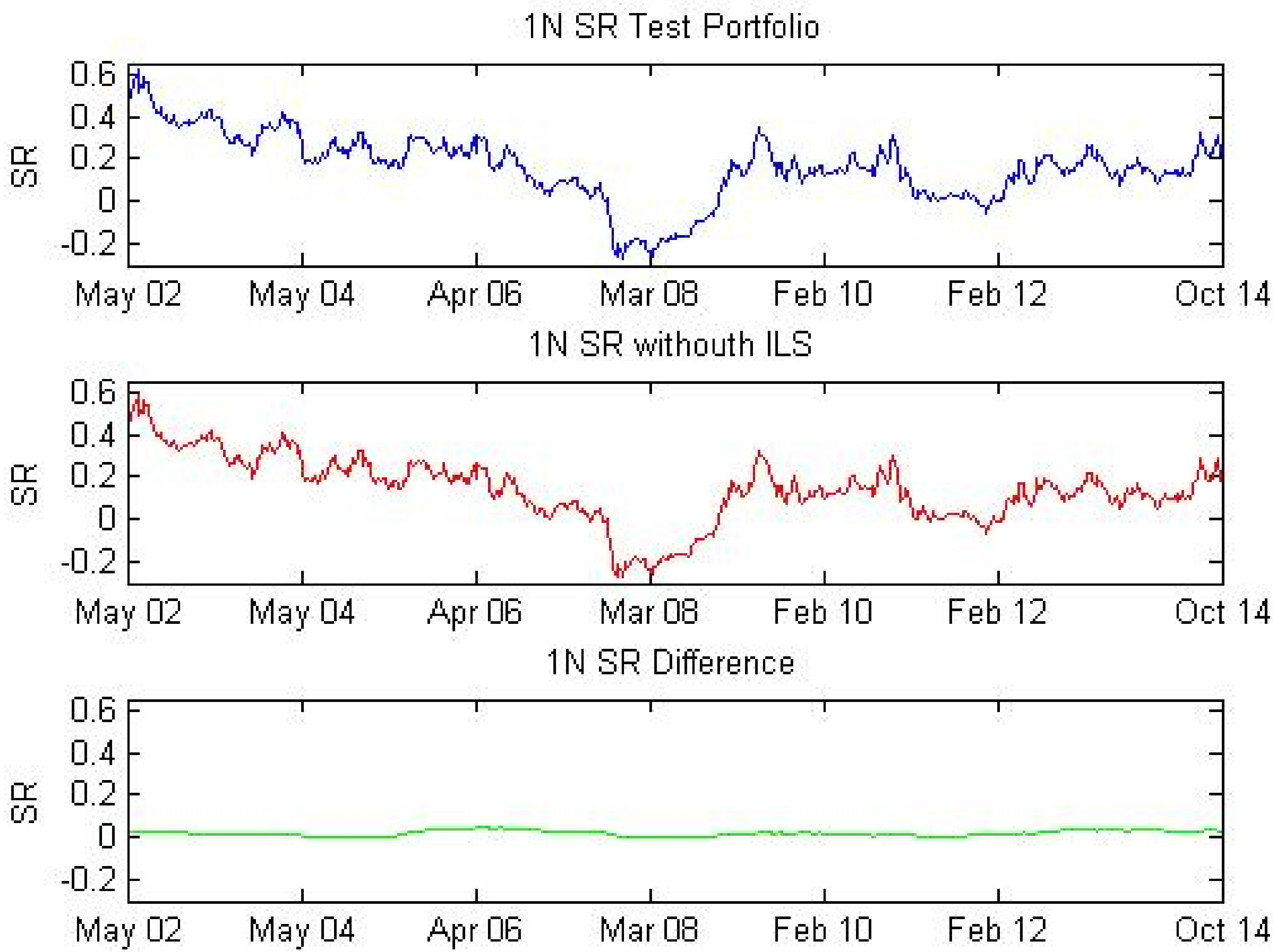

Figure 4: Rolling Sharpe Ratios for Max Sharpe Ratio

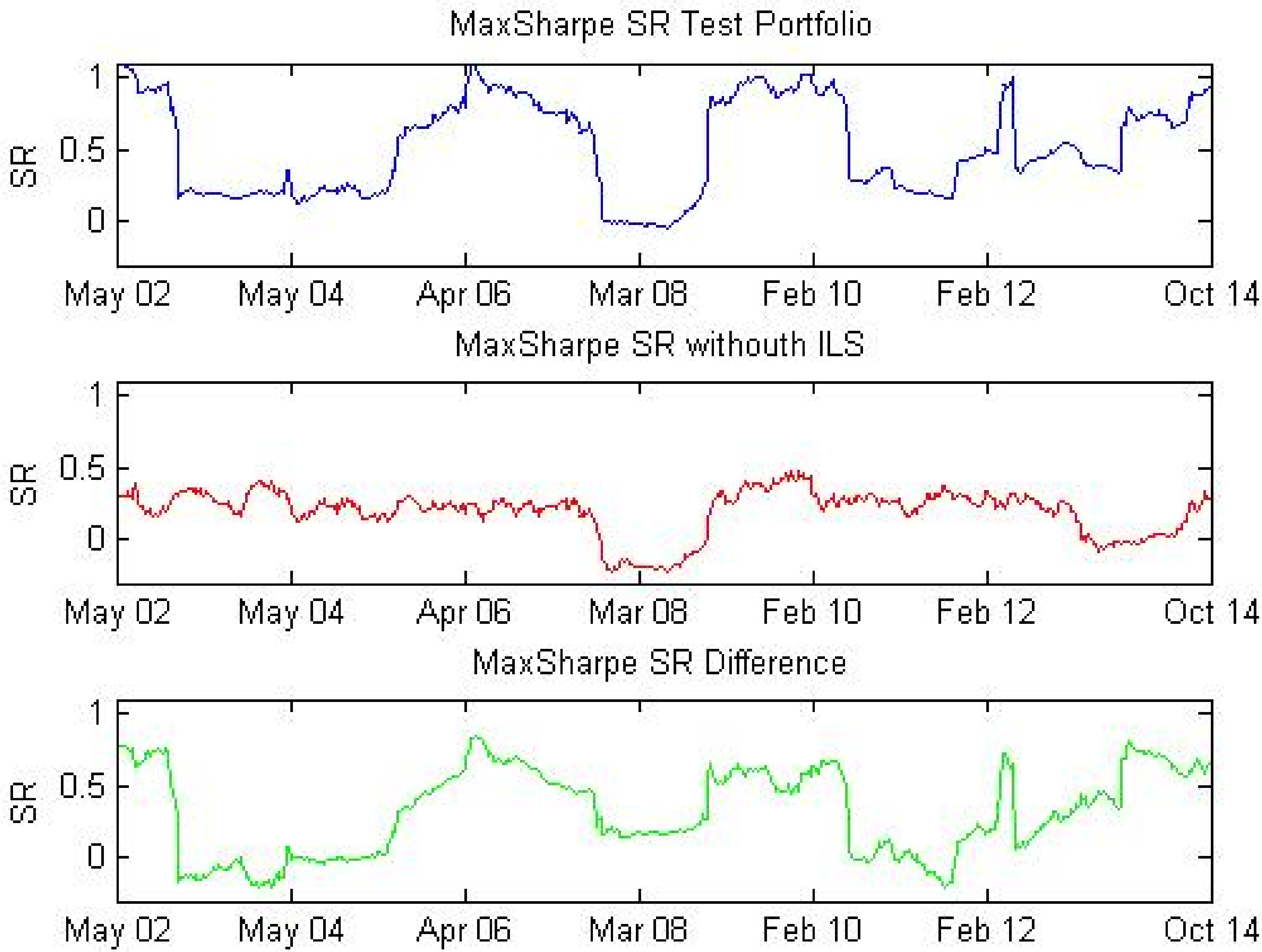

Figure 5: Rolling Sharpe Ratios Differences for All Strategies