Bear Market Risk and the Cross-Section of Hedge Fund Returns*

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ABSTRACT

We examine the presence of a premium for bear market risk – innovation in the probability of future bear market states – in the cross-section of hedge fund returns. Bear beta, the sensitivity of hedge funds to returns of a bear spread portfolio controlling for the market, is a direct way to classify funds as insurance buyers or sellers. We find that low bear beta funds (insurance sellers) outperform high bear beta funds (insurance buyers) by 0.58% per month on average, outperform even during market crashes, but underperform when bear market risk is realized. This contradicts the conventional belief that insurance sellers should be more exposed to realized crash risk.

JEL Classification: G11, G12, G23

Keywords: hedge funds, bear market risk, bear beta, Bear factor, market-hedged Bear factor

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1. Introduction

In a seminal paper, Agarwal, Ruenzi, and Weigert (2017) show that the hedge funds with positive sensitivity to market tail risk outperform hedge funds with no sensitivity to tail risk on average but underperform in periods of negative market returns. Moreover, they find that tail risk exposure arises naturally because several popular hedge fund trading strategies resemble the provision of out-of-the money put options on the equity market index. This has given rise to a conventional wisdom that certain hedge funds tend to act more as insurance sellers, collecting an insurance premium in good times (i.e. in most of the cases) and experiencing substantial losses in bad times (i.e. in a few cases). However, return behaviors of hedge funds acting as insurance buyers are often ignored. We find that hedge funds who seek insurance tend to have very high market exposure beforehand, but they only hedge part of their portfolio, leaving a significant part of their market exposure unhedged. For these funds, buying insurance does not help avoid losses during market crashes. Therefore, the fact that *an average* high-tail risk funds tend to act as insurance sellers does not mean that tail risk exposure can always be seen as an accurate representation of the extent to which hedge funds act as insurance buyers or sellers.[1]

In this paper, we argue that by trading insurance, buyers and sellers are exposed to a different kind of systematic risk – bear market risk – that explains their relative performance in the cross-section. Bear market risk captures the change in ex ante concerns about future bear market states and thus, is distinct from the present realizations of downside states. Specifically, we estimate the sensitivity of each hedge fund's returns to the returns of a put options portfolio controlling for the market factor. Intuitively, hedge funds with positive (negative) bear betas are interpreted as insurance buyers (sellers). Importantly, the returns of hedge funds who buy (sell) insurance can also be seen as a combination of unhedged market exposure and long (short) market-hedged insurance exposure .[2] We further find that both buyers and sellers

[1] Here we do not mean that certain hedge funds actually write insurance contracts to other funds. Instead, we posit that the trading activity of hedge funds through the usage of options, leverage, short sales etc. leads to payoffs that are effectively close to an insurance buying or selling strategy (see also, Stulz, 2007; Ang, 2014; Gao, Gao and Song, 2018). Hedge funds that act as insurance buyers are referred to as "black swan" funds in the financial press.

[2] We later show that controlling for the market factor is a necessary condition for correctly categorizing hedge funds. If we do not control for the market, insurance buyers cannot be correctly identified. The reason is that insurance buyers still have positive market exposure, while the put portfolio and market factor are highly negatively correlated. As a result, the exclusion of the market factor

have positive but almost identical unhedged market exposure. As a result, any systematic difference in their expected returns should be the outcome of their differential exposure to the market-hedged insurance return. This hedged part return captures the movement of the insurance price relative to the market that has a different behavior from the movement of the insurance price alone. We define that this hedged part return reflects the change in ex ante concerns about future bear market states. Intuitively, when concerns about future bear market states increase, the increase (decrease) in insurance premium is more (less) than the decrease (increase) in market price, and vice versa.

In this respect, the belief that hedge funds acting as insurance sellers experience worse returns during market crashes by being exposed to tail risk is too simplistic in the cross-section. The above interpretation is entirely accurate only if the return of a portfolio insurance strategy always exceeds (the absolute value of) the negative market return. In a recent study, Lu and Murray (2019) provide a clear evidence that this is not the case. In particular, they find that a severe market decline is quite often accompanied by an increase in the price of portfolio insurance that is less than it should be. Indeed, while the returns of the market insurance are strongly affected by market movements, these two do not necessarily coincide. It is possible that there is a high increase in investors' fears about future bear market states even if there is little or no negative market return. In this case, the gain (loss) for the insurance buyer (seller) is high. In the same vein, it is possible to have little increase in the price of market insurance even if there is a large negative market return. In such a case, the buyer (seller) is actually worse off (better off). Therefore, the market-hedged insurance returns capture the change in ex ante concerns about future bear market states on top of what is justified by concurrent market returns. Accordingly, exposure to bear market risk is distinct from exposure to tail risk, which instead aims to capture hedge fund reaction to a realized crash event. Empirically, we show that the hedged position has a significantly negative premium on average, and its return is still negative during market crashes. This implies the outperformance of insurance sellers relative to insurance buyers on average and even during market tail events.

Overall, we argue that by trading insurance, buyers and sellers are exposed to bear market risk, a distinct concept from tail risk. We hypothesize that insurance sellers generate higher average returns relative to

from the bear beta estimation regression leads to a situation where the market exposure dominates the put portfolio exposure and the bear beta turns negative instead of positive.

insurance buyers by being more exposed to bear market risk, while at the same time they may not always be more exposed to realized tail risk. Our hypothesis is based on the notion that assets that pay off when there is an increasing concern about future bear market states should earn lower average returns because they serve as hedging instruments. We argue that hedge funds behave much like conventional assets in this economy, earning a premium by being exposed to bear market risk and vice versa. Our empirical analysis provides strong support in favour of this argument.

We follow Lu and Murray (2019) to capture the probability of future bear market states by constructing an Arrow (1964) and Debreu (1959) portfolio, or Bear portfolio, from traded S&P 500 index options. Such a portfolio has the advantages of being economically intuitive, model-free, and tradable. More specifically, the Bear portfolio is a bear spread position in S&P 500 index put options, which is long an out-of-the-money (OTM) put, and short a further OTM put. Because this bear spread position will pay off $1 if the market at expiration is in a bear state, its price reflects a forward-looking measure of the risk-neutral probability of future bear market states and its short-term return captures the variation in this probability.[3] We create a monthly Bear factor from the one-month buy-and-hold excess returns of the Bear portfolio.[4] We measure hedge fund bear beta as the loading on the Bear factor from a regression of the hedge fund excess returns on the Bear factor and the excess market returns. This is equivalent to regressing fund excess returns on the Bear factor orthogonalized to the market returns. This market hedged Bear factor is negative on average due to the premium paid for buying bear market risk insurance and is still negative during the periods with the lowest market returns. Overall, it captures time-variation in the probability of future bear market states without being exposed to market movements (see also Lu and Murray, 2019).

To empirically test the explanatory power of bear beta for the cross-section of future hedge fund returns, we sort hedge funds based on their bear beta, group them into quintiles, and examine the average returns of

[3] We later show that the results are robust to using a portfolio consisting of a long-only put option. Similar to Lu and Murray (2019), we prefer to use the Bear portfolio in the main analysis for several reasons. First, its return has a clear economic interpretation. Second, the price of a portfolio that combines long and short put positions is less affected by demand pressure forces than the price of a portfolio consisting of a long-only put (Bollen and Whaley, 2004; Garleanu, Pedersen and Poteshman, 2009). Third, in practical terms, the return of a combined long-short put position is less impacted by unrelated factors such as the time decay of the options.

[4] It is important to note that the Bear portfolio is not held until the maturity date. While the hold-to-maturity return is determined by the market state at the option expiration date, the shorter-term return represents the change in ex-ante probability of future bear market states.

these quintiles over the next one month. We find that hedge funds in the most negative bear beta quintile – funds whose trading strategies are more associated with selling bear market risk insurance – have an average monthly return that is 0.58% higher than hedge funds in the most positive bear beta quintile – funds whose trading strategies are more associated with buying bear market risk insurance. The risk-adjusted return spread between the high and low bear beta quintiles remains significant based on the Fung and Hsieh (2004) seven-factor model as well as other performance evaluation models used in the asset pricing literature. The results also hold for value-weighted portfolios and the predictive power of bear beta for future hedge fund returns extends as far as 18 months ahead.

Our conditional portfolio-level analysis during periods of market crashes, defined as months when the market returns are lower than its tenth percentile over the sample period, reveals that both insurance buyers and sellers earn negative excess returns, consistent with both having positive unhedged market exposure.[5] Interestingly, insurance buyers experience greater losses, consistent with the market hedged Bear factor being negative even during the most negative market return periods. Therefore, hedge funds in the most positive bear beta quintile underperform those in the most negative bear beta quintile by 2.85% on average during these months. The result is contrary to an implicit, but untested, assumption that an average insurance buyer should earn positive return when the market significantly declines. Furthermore, we still observe the outperformance of insurance sellers by an average of 1.16% per month when the market excess returns are negative. These findings lend further support to the idea that hedge funds who act insurance sellers are not necessarily more exposed to realized market tail risk.

We further investigate whether the negative relation between bear beta and future hedge fund returns can be explained by other fund characteristics or exposure to alternative risk factors by performing a series of multivariate Fama and MacBeth (1973) regressions. The results confirm that bear beta predicts future fund returns after controlling for various fund characteristics such as fund size, age, management and incentive fee, lockup and redemption period and leverage, as well as past fund return and its higher moments. Further tests controlling for variables capturing manager skills and hedge fund exposure to risk factors such as risk-neutral moments, and market tail risk cannot subsume the fund-level cross-sectional relation between bear

[5] The finding is also consistent with the notion that hedge fund industry as a whole is exposed to substantial market downturns.

beta and future returns. Therefore, hedge fund exposure to bear market risk is distinct from exposure to tail risk as well as other previously documented risk factors.

As low bear beta funds earn higher returns on average by being more exposed to bear market risk, we should observe an opposite, i.e. positive, relation between bear beta and hedge fund returns during times of high bear market risk. We define high bear market risk periods as months when the market hedged Bear factor – the component of the Bear factor that is orthogonal to the market – is positive. In essence, the increase (decrease) in the price for market insurance is higher (lower) than what would be justified by the concurrent negative (positive) market return. During these months, we observe a strong positive relation between bear beta and future hedge fund returns. In contrast, during the remaining months, the relation is negative and statistically significant.

We next examine the determinants of hedge fund bear beta. Several findings are in line with prior evidence on the risk-taking behavior of hedge funds. First, high exposure to bear market risk (low bear beta) is associated with funds that are young, exhibit negative return skewness, and have higher past return. The results support the notion that young funds might have an incentive to attract fund flows by establishing a track record of high returns early in their life cycle. Second, funds with higher exposure to bear market risk are more likely to demand higher management fees and have a hurdle rate, which is consistent with risk-taking behavior responding to incentives. However, as previously discussed, hedge fund characteristics cannot fully explain the negative relation between bear beta and future fund returns.

In a related study, Gao, Gao and Song (2018) use a portfolio of put options to capture investors' concerns about future disaster risk (RIX). They find that hedge funds with high RIX betas earn on average higher returns than funds with low RIX betas and interpret this as an indication that high RIX beta funds possess skills in exploiting disaster concerns. While the put portfolio in their study is different from ours, the two portfolios are conceptually similar. Therefore, at a first glance their results look opposite to ours. The reason for this ostensible difference comes from the fact that Gao, Gao and Song (2018) use the average daily price of the put options portfolio within a month rather than the monthly return as we do. In particular, we show that the sensitivity to the return – and not to the price level – of the same S&P500 index put portfolio that is used in the RIX construction predicts future hedge fund returns negatively. Furthermore, in line with our main empirical evidence, we still observe the negative relation even when the market crashes, implying that insurance sellers still outperform insurance buyers during this period. However, we do not find evidence that the sensitivity of hedge fund to this RIX return factor absorbs the relation between RIX betas and future hedge fund returns. Overall, the conclusions of the two studies are not inconsistent with each other. It is perfectly possible that the two effects, i.e. insurance sellers exploiting cases of overpriced insurance as Gao, Gao and Song (2018) suggest and insurance sellers earning high returns by just being exposed to bear market risk as we suggest, coexist and complement each other.

Our study is related to a strand of the literature that relies on the differential exposure of hedge funds to option-implied risk factors in order to explain their returns in the cross-section (see, for example, Agarwal, Bakshi, and Huij, 2010; Buraschi, Kosowski, and Trojani, 2014; Agarwal, Arisoy, and Naik, 2017).[6] We contribute to this literature by identifying a channel through which hedge funds are exposed to bear market risk and proposing the sensitivity to the market hedged Bear portfolio – the bear beta – as a direct and novel way to study the return behavior of hedge funds that act as insurance buyers or sellers. We further show that bear beta is one of the strongest predictors for the cross-section of hedge fund returns and this predictability is in line with standard asset pricing intuition.

Finally, we also contribute to the literature that aims to uncover the determinants of hedge funds' tail risk. Jiang and Kelly (2012) and Agarwal, Ruenzi, and Weigert (2017) postulate that hedge funds whose trading activities resemble insurance selling (buying) are more (less) adversely affected by realized market crashes. Our evidence suggests that this relation is not always valid though. We suppose that market tail events do not play a significant role in explaining the relative return difference between insurance buyers and sellers who involve in hedging their existing positions rather than buying or selling naked put options on the market. More specifically, we show that insurance sellers underperform insurance buyers only when the market crash is accompanied by a high increase in the price of insurance. If this is not the case, insurance sellers continue to outperform insurance buyers.

The rest of the paper is organized as follows. The next section discusses the data, construction of the Bear portfolio, and hedge fund bear beta measure. Section 3 presents the main results of the paper by studying

[6] In the time-series, a number of studies, such as Fung and Hsieh (1997), Fung and Hsieh (2001), Amin and Kat (2003), Agarwal and Naik (2004), Agarwal, Bakshi, and Huij (2010), Jurek and Stafford (2015), and Agarwal, Arisoy, and Naik (2017), demonstrate option-like features inherent in the time-series return behavior of many hedge fund investment styles.

the performance of bear beta-sorted hedge fund portfolios, examining whether the effect of bear beta on future hedge fund returns is subsumed by other fund characteristics and risk measures, and investigating the predictability across different market states. Section 4 studies the determinants of bear beta. Section 5 provides additional analyses. We perform a series of robustness checks in Section 6 and conclude in Section 7.

2. Data and Variable Construction

2.1. Hedge fund data

The hedge fund data, including monthly hedge fund returns and fund characteristics, are from the Hedge Fund Research database (HFR), which is one of the leading sources of hedge fund information. In this database, we originally have information on a total of 25,976 live and defunct hedge funds. Since we construct the Bear portfolio returns using option data from OptionMetrics that are available from January 1996, the full sample period of hedge fund returns that we use in this study is from January 1996 to December 2017. Following the literature, we retain monthly-filing funds and funds that report returns net of all fees and in US dollars.

Next, we make efforts to minimize the effects of potential data biases documented in the hedge fund literature (Fung and Hsieh, 2000; Liang, 2000; Edwards and Caglayan, 2001). First, to mitigate the backfilling bias, we follow Kosowski, Naik, and Teo (2007) to eliminate the first 12 months of a fund's return series. Furthermore, since this problem might be prevalent among small funds, we discard all funds with less than $10 million of asset under management (AUM). Specifically, if a fund begins with less than $10 million but later has $10 million in AUM, we include the fund in the sample from the time its AUM reaches $10 million and keep it in the sample as long as the fund exists regardless of its AUM. Second, monthly return histories of both live and defunct funds over the sample period from January 1996 to December 2017 are included, which helps minimize the survival bias. In Section 6, we perform a robustness check where we assume that returns of drop-out funds are -100% following their last reporting month.

The above process leaves us with a final sample of 11,084 distinct hedge funds, of which 8,190 are defunct funds and the remaining 2,894 are live funds. We follow Joenväärä, Kauppila, Kosowski and Tolonen (2019) to categorize hedge funds into ten primary strategies: event-driven, relative value, long-short equity, global macro, CTA, equity market-neutral, short-bias, sector, and fund of funds. In terms of the number of funds, long-short equity is the largest strategy style, comprising 2,936 distinct hedge funds in our sample, whereas there are only 60 hedge funds falling into the short bias strategy group. Table 1 presents descriptive statistics for our hedge fund sample.

[Insert Table 1 here]

Panel A of Table 1 reports the time-series average of the monthly cross-sectional mean, standard deviation, and percentiles of all individual hedge fund returns. On average, a fund earns 0.64% per month over the sample period 1996-2017 with a standard deviation of 4.03%. Among ten main strategy categories, Sector and Long-short Equity are two strategies that yield the highest average monthly returns, 0.97% and 0.78% respectively, while Short-bias hedge funds realize the lowest performance with an average return of -0.15%.

In Panel B of Table 1, we present the year-by-year number of funds entering the database, number of funds dissolved, total AUM, and distribution statistics of the monthly equal-weighted hedge fund portfolio returns. The period 1996-2007 experienced an exponential increase both in number of operating hedge funds, from 764 in 1996 to 4,583 funds at the end of 2007, and in total AUM, from around $109 billion in 1996 to $1,549 billion in 2007. However, there was a sharp reversal in both of these figures, coupled with an increase in yearly attrition rates (ratio of the number of dissolved funds to the total number of funds at the beginning of the year) starting in 2008 due to the effect of the financial crisis. By the end of 2017, there were 2,894 operating hedge funds with total AUM of $1,211 billion in our sample.

Panel C reports distribution statistics of cross-sectional hedge fund characteristics. The average AUM of individual hedge funds in our database is $171 million while the median size is $49 million, implying that there are a few hedge funds with very large size. On average, an individual hedge fund operates for approximately 78 months or 6.5 years. Management fee and incentive fee are 1.44% and 15.78% on average, respectively. Hedge funds in our sample have an average lockup period of 3.46 months and require an average minimum investment of $1.26 million.

2.2. Bear portfolio

2.2.1. Data

Data for S&P500 index options, including daily closing bid and ask quotes, trading volume and open interest for the period from January 1996 to December 2017, are obtained from OptionMetrics. We further collect the daily S&P500 index level and dividend yield, the VIX index level, and the risk-free rate. We apply several filters to the option data. First, to avoid illiquid options, we discard options if open interest is zero or missing, if the bid quote is zero, or if the bid quote is smaller than the ask quote. Second, all options that violate no-arbitrage conditions are excluded. Specifically, for a put option we require that the exercise price exceeds the best bid, which is in turn higher than $max(0, K - S_0)$, where K and S_0 are the option's strike price and the closing level of the S&P500 index respectively. Third, we only keep options with standard expiration dates.

We use the mid-point of the bid and ask quotes as a proxy for the market price of the option contract. We further define the S&P 500 index forward price to be $F = S_0 e^{(r-y)T}$, where r is the continuously compounded risk-free rate, y is the dividend yield of the S&P 500 index, and T is the time to maturity.

2.2.2. Bear portfolio construction

We follow Lu and Murray (2019) and define an Arrow-Debreu bear security as a portfolio that pays $1 when the S&P 500 index level on a given date is in a bear state, and zero otherwise. We approximate this payoff structure from traded options by taking a long position in a put contract with strike price $K_1 > K_2$ and a short position in a put contract with strike price K_2. After scaling both positions by $K_1 - K_2$, the Bear portfolio will generate a payoff of $1 at expiration if the index level is below K_2 and zero if the index level is above K_1. The payoff decreases linearly from $1 to zero for index levels at expiration falling between K_2 and K_1. Thus, the Bear portfolio price, P_{Bear}, is:

$$P_{Bear} = \frac{P(K_1) - P(K_2)}{K_1 - K_2}, \tag{1}$$

where $P(K)$ is price of a put option with strike price K.

We choose K_2 to be 1.5 standard deviations bellow the S&P 500 index forward price. The strike price K_2 establishes the bear region boundary, meaning that the market is in bear state when the market excess return is more than 1.5 standard deviations below zero.[7] K_1 is set to be one standard deviation below S&P 500 index forward price.[8]

The standard deviation of the market return is defined as $V\sqrt{T}$, where V is the VIX index level divided by 100. Setting the standard deviation equal to VIX instead of using a constant volatility means that the bear market region under consideration is always adjusted for current market volatility levels. As a result, the price of the Bear portfolio, i.e. the discounted risk-neutral probability of a bear market outcome, remains roughly the same at each portfolio formation period. The return of the portfolio captures innovations in bear market concerns.

In the same vein with Lu and Murray (2019), we define $P(K_1)$ and $P(K_2)$ to be the trading-volume weighted average price of puts with strike prices within a 0.25 standard deviation range of the target strikes, K_1 and K_2. We follow this procedure because traded option contracts with exact targeted strikes are unlikely to exist. In addition, the volume-weighted average put price over a range of strikes gives more weight to liquid put options whose prices are expected to be less affected by microstructure noise. More specifically, we take:

$$P(K_1) = \sum_{K \in \left[F.e^{-1.25\frac{VIX}{100}\sqrt{T}},\ F.e^{-0.75\frac{VIX}{100}\sqrt{T}}\right]} P(K).w(K) \tag{2}$$

and

$$P(K_1) = \sum_{K \in \left[F.e^{-1.75\frac{VIX}{100}\sqrt{T}},\ F.e^{-1.25\frac{VIX}{100}\sqrt{T}}\right]} P(K).w(K)\,, \tag{3}$$

where $w(K)$ is the trading volume of a put option with strike price K divided by the total trading volume of all put options in the indicated range.

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[7] The 1.5 standard deviations point is chosen based on a trade-off between our objective of capturing significant downward market movements on the one hand, and the relative illiquidity of deep-out-of-the-money put options on the other hand. In Section 6, we show that the findings are very similar if we use different definitions of bear market regions.

[8] Although as K_1 approaches K_2, the payoff function of the Bear portfolio converges to the theoretical payoff of an Arrow-Debreu security, the spread between $P(K_1)$ and $P(K_2)$ also converges to zero and might be adversely affected by noise from option bid-ask spreads. Choosing $K_1 - K_2$ to be half a standard deviation is based on a trade-off between these two considerations.

2.2.3. Bear portfolio returns

Since returns of individual hedge funds in our database are available on a monthly basis, we also create a monthly Bear portfolio return factor. Specifically, on the last trading day of each month from January 1996 to November 2017, we buy the Bear portfolio using put options that have the shortest maturity among those with more than one month to expiration and calculate its price using the averages of closing bid-ask quotes of these options.[9] We hold the portfolio for one month and measure its excess return by subtracting the one-month risk-free rate from the one-month buy-and-hold return. In total, there are 264 monthly Bear portfolio excess returns for the period over 1996-2017.

[Insert Table 2 here]

Table 2 reports the descriptive statistics for the monthly times-series of the Bear factor. Following Lu and Murray (2019), we scale the Bear factor to have the same volatility with the market factor. The average monthly excess return of the Bear factor is -1.64% and is statistically significant with a t-statistic of -5.04 (as shown in the first column in Panel B of Table 2). The Bear portfolio returns exhibit a noticeably right-skewed distribution with a skewness of 2.64.

We further investigate whether the significantly negative Bear portfolio excess return is the compensation for exposure to previously identified risk factors. In Panel B of Table 2, we perform time-series regressions of the Bear factor, $r_{BEAR,t}$, on contemporaneous risk factor returns, $\boldsymbol{F}_t$, over January 1996 to December 2017. The regression is defined as:

$$r_{BEAR,t} = \alpha + \boldsymbol{\beta}' \times \boldsymbol{F}_t + \varepsilon_t, \tag{4}$$

where $\boldsymbol{\beta}$ captures the exposure of the Bear factor to standard risk factors and α measures the average Bear portfolio excess return that is not explained by the risk factors.

In Model 2 of Panel B, we regress the Bear portfolio returns on the market excess returns. Consistent with its negative delta exposure, the Bear factor exhibits a significant market exposure with a coefficient on the

[9] For example, on 31/01/1996 we choose options that expire on 16/03/1996 to create the Bear portfolio. Out of 264 months, there are nine months for which we do not have available put options that meet these requirements. For these months, we form the Bear portfolio on the first trading day of the month (instead of the end of last month) and hold it until the month end.

market factor of -0.85 (t-statistic of -15.90) and an adjusted R^2 of 72%. However, the average alpha after controlling for the market factor is -1.09% per month, which is statistically significant with a t-statistic of -6.77. The finding implies that market factor exposure cannot fully capture the negative average return of the Bear portfolio.

In addition, the Bear factor is not subsumed by other standard risk factors documented in the asset pricing and hedge fund literature. In Models 3 and 4 of Panel B, we regress the monthly Bear portfolio excess returns on the Fama-French (1993) three factors and Carhart (1997) four factors (three-factor model augmented with a momentum factor) respectively. We find that the Bear portfolio still yields significantly negative alpha relative to these asset pricing models. We further examine whether the Bear factor is captured by the Fung and Hsieh (2004) seven factors. As shown in Model 5, the Bear portfolio produces an average alpha of -0.89% per month (with a t-statistic of -5.13) relative to the Fung and Hsieh (2004) seven-factor model. Finally, Model 6 shows that the negative excess return of the Bear portfolio cannot be explained by the Fung and Hsieh (2004) seven factor model augmented with the value and momentum factors. In fact, as indicated by the small changes in R^2, factors other than the market have little explanatory power over the Bear factor.

2.3. Hedge fund exposure to bear market risk

We measure a hedge fund's sensitivity to bear market risk as follows. At the end of each month from December 1997 to November 2017, and for each hedge fund, we run a time-series regression of the fund's monthly excess returns on the market excess returns and the Bear factor over a 24-month rolling-window period:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{BEAR} \times r_{BEAR,t} + \epsilon_{i,t}, \quad (5)$$

where $r_{i,t}$ is the excess return of fund i in month t, MKT_t is the contemporaneous CRSP value-weighted market excess return, and $r_{BEAR,t}$ is the contemporaneous Bear factor return. We require at least 18 months of non-missing fund returns to ensure that we have a sufficient number of observations in the estimation.

Our main variable of interest is the hedge fund bear beta, $\beta_{i,t}^{BEAR}$, which captures the fund's exposure to the component of the Bear portfolio return that is orthogonal to the market return. This orthogonal component (market hedged Bear factor) is basically the return of the Bear portfolio hedged with respect to the market return and is equivalent to the intercept plus the residuals from a regression of the Bear portfolio returns on the market returns:

$$r_{BEAR,t} = \gamma + \delta \times MKT_t + \eta_t = r_{HEDGED\_BEAR,t} + \delta \times MKT_t. \tag{6}$$

As shown in Section 2.2, this intercept coefficient (γ) is negative on average.

[Insert Figure 1 here]

Figure 1 plots the monthly market hedged Bear factor over the period from January 1998 to December 2017. The return for each month t is obtained from a rolling regression of the Bear factor on the market factor over the past 24 months. The five highest (positive) market hedged Bear portfolio returns happen in August 1998, September 2000, February 2001, April 2002, and May 2012. During these months, the market excess returns were, -16.08%, -5.45%, -10.05%, -5.20%, and -6.19%, respectively. While these returns are all negative, with the exception of August 1998, those months are not the ones that experience the largest market losses. In fact, the average hedged Bear portfolio return in the five months with the largest negative market returns over 1998-2017 is -0.63%, which is negative.

These results are indicative of an important observation. While market returns and investors' bear market concerns are highly negatively correlated on average, they do not move in lockstep. It is possible that a negative market return is accompanied by a slightly positive (highly positive) Bear portfolio return. In this case, the market hedged Bear factor return will be negative (positive). Similarly, a positive market return might be accompanied by a highly negative (a slightly negative) Bear portfolio return. In this case, the market hedged Bear factor return will be negative (positive). Therefore, the market hedged Bear factor reflects the increase in investors' concerns about future bear market states on top of what is justified by concurrent market returns. In that respect, the estimated hedge fund bear betas contain different information from hedge funds' exposure to realized market tail risk.

[Insert Table 3 here]

While the interpretation of the market hedged Bear factor itself is straightforward, it is useful to clarify why it is important to estimate hedge funds' sensitivity to bear market risk using the market hedged Bear factor, i.e. estimating Equation (5) which controls for the market. Panel A of Table 3 presents the average bear beta, $\beta_{i,t}^{BEAR}$, and market beta, $\beta_{i,t}^{M}$, of portfolios sorted on bear beta. Intuitively, the high bear beta hedge funds act as insurance buyers, while the low bear beta hedge funds act as insurance sellers. We observe that insurance buyers have a high market beta of 0.89, while the insurance sellers have a slightly negative market beta of -0.04. This result is reasonable in the sense that the hedge funds that seek insurance are the ones already having some high exposure to the market. However, these market beta values ignore that fact that the market and the Bear portfolio are highly negatively correlated. In fact, an insurance buyer (seller) reduces (increases) his overall market exposure by being long (short) the Bear portfolio. By combining Equations (5) and (6) we get:

$$r_{i,t} = \alpha_{i,t} + \left(\beta_{i,t}^{M} + \beta_{i,t}^{BEAR} \times \delta\right) \times MKT_t + \beta_{i,t}^{HEDGED\_BEAR} \times r_{HEDGED\_BEAR,t} + \epsilon_{i,t}. \tag{7}$$

This means that the total risk exposure of a hedge fund can be seen as the combination of its unhedged market exposure and its exposure to the market hedged Bear factor. Panel B of Table 3 shows that the average unhedged market exposures, $\beta_{i,t}^{MKT} = \left(\beta_{i,t}^{M} + \beta_{i,t}^{BEAR} \times \delta\right)$, of the low and high bear beta hedge funds are almost identical, at 0.43. Collectively, the results can be interpreted as follows. Both insurance buyers and insurance sellers behave as if they are similarly exposed to the market factor, but insurance buyers obtain also a hedged long position to the market, while insurance sellers obtain also a hedged short position to the market. In that respect, any difference in their relative performance should be attributed to their differential exposure to the market hedged Bear factor. In other words, hedge funds with low bear betas are expected to earn the negative premium of the market hedged Bear factor, and hence outperform on average the high bear beta hedge funds that pay the premium.

There is also a second reason for which it is important to control for the market when estimating hedge fund exposure to bear market risk. In particular, if we do not do so, it will be impossible to correctly identify insurance buyers. As discussed above, high bear beta funds have a high positive market beta and the Bear portfolio and market factor are highly negatively correlated. Therefore, if the market factor is excluded from Equation (5), the large positive exposure of insurance buyers to the market will dominate the positive exposure to the Bear portfolio and the bear beta will turn negative. It is easy to see this by combining:

$$MKT_t = \rho + \lambda \times r_{BEAR,t} + \zeta_t, \tag{8}$$

with Equation (5) to get:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times \rho + \left(\beta_{i,t}^{BEAR} + \beta_{i,t}^{M} \times \lambda\right) \times r_{BEAR,t} + \beta_{i,t}^{M} \times \zeta_t + \epsilon_{i,t}, \quad (9)$$

and noting that λ is typically a number between -0.85 and -0.90, while in the case of insurance buyers the average $\beta_{i,t}^{BEAR}$is equal to 0.53 and the average $\beta_{i,t}^{M}$ is equal to 0.89. In fact, Panel C of Table 3 shows that ignoring the market factor would cause the bear beta of insurance buyers, $\beta_{i,t}^{UNHEDGED\_BEAR} = \left(\beta_{i,t}^{BEAR} + \beta_{i,t}^{M} \times \lambda\right)$, to become negative, at -0.27. The problem is much less acute in the case of insurance sellers. Their bear beta estimated ignoring that market factor takes the value of -0.51, which is similar to the value of -0.55 found when controlling for the market. The reason is that the average $\beta_{i,t}^{M}$ of insurance sellers is close to zero, at -0.04, and hence $\left(\beta_{i,t}^{BEAR} + \beta_{i,t}^{M} \times \lambda\right)$ is a number very close to $\beta_{i,t}^{BEAR}$.

3. Bear market risk and hedge fund performance

So far, we had shown that systematic difference in relative performance of insurance sellers and buyers comes from their differential exposure to the market hedged Bear factor – a proxy for bear market risk. This hedged factor is negative on average and is not correlated with market movement. Equivalently, we hypothesize that hedge funds with negative bear betas – whose strategies resemble selling insurance – outperform on average by earning the negative premium of the market-hedged Bear factor without being more exposed to market crashes. Instead, they underperform when concerns about future bear market states increase.

3.1. Portfolio-level analysis

3.1.1. Unconditional analysis

At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles based on bear beta. The fifth (first) quintile consists of funds with the highest (lowest) bear betas. We also form a portfolio that goes long hedge funds in the fifth quintile and short hedge funds in the first quintile. We hold the portfolios for one month and measure their returns, which are from January 1998 to December 2017.

[Insert Table 4 here]

Panel A of Table 4 reports the results for the performance of hedge fund portfolios sorted by bear beta. In particular, we present the time-series average of hedge fund returns across five quintiles. Each quintile has about 500 hedge funds on average and is well diversified. The average monthly equal-weighted hedge fund portfolio returns decline monotonically from 0.87% in the lowest bear beta quintile to 0.29% in the highest bear beta quintile. The average return difference between quintile 5 and quintile 1 is -0.58% per month, or -6.99% per year, with a t-statistic of -3.53. To measure portfolio-level risk-adjusted abnormal returns (alphas), we perform a time-series regression of the monthly hedge fund portfolio returns in each quintile on the Fung and Hsieh (2004) seven factors, including three trend-following, two equity-oriented, and two bond-oriented risk factors (i.e. *FTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET,* and *BAAMTSY*). The regression is generally defined as:

$$r_{P,t} = \alpha_P + \boldsymbol{\beta_P}' \times \boldsymbol{F}_t + \varepsilon_{P,t}, \tag{10}$$

where $r_{P,t}$ is month t hedge fund portfolio return in each quintile. We find that the Fung-Hsieh 7-factor alpha of the lowest bear beta portfolio is 0.70% (with a t-statistic of 4.04) while that of the highest bear beta portfolio is only -0.02% (with a t-statistic of -0.17). The resulting spread between alphas of quintile portfolios 5 and 1 is -0.72% per month and is significant at all conventional levels with a t-statistic of -3.73.

We further examine whether the return spread between quintile 5 and 1 can be explained by additional hedge fund risk factors. We modify equation (10) by regressing equal-weighted Q5-Q1 portfolio returns on the Fung-Hsieh (2004) and several additional risk factors. The results are presented in Panel B of Table 4.

For ease of comparison, we report the results of the Fung and Hsieh (2004) seven-factor model as our baseline specification in the first column. These seven factor returns explain only 12% of the total variation in return difference between Q5 and Q1 over the period and none of them has a significant coefficient. In the second column, we include the HML (high-minus-low) and UMD (up-minus-down) factors from the Carhart (1997) model to control for book-to-market and momentum. In column 3, we further add the Pastor and Stambaugh (2003) traded liquidity factor to control for liquidity exposure of hedge funds. In columns 4 to 7, we respectively include the returns of a long-short hedge fund portfolio with respect to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor, the Agarwal, Bakshi, and Huij (2010) risk-neutral volatility and skewness factors, the Gao, Gao, and Song (2018) RIX factor, and the Agarwal, Ruenzi, and Weigert (2017) tail risk measure. In column 8, we add all previously discussed factors. Importantly, our results indicate a significant negative alpha (or risk-adjusted return) for the Q5-Q1 return spread that ranges from -0.49% to -0.72% per month with the t-statistic ranging from -2.93 to -4.04.

To summarize, there is a negative cross-sectional relation between exposure to bear market risk and expected hedge fund returns. Equivalently, hedge fund managers who choose to harvest the risk premium from selling bear market risk insurance earn higher average returns than those who buy the bear market risk insurance. Their significant outperformance cannot be explained by the exposure to standard risk factors documented in the hedge fund literature.

3.1.2. Conditional analysis

To examine whether hedge funds with low bear betas – whose trading strategies are associated with selling insurance – are more or less exposed to market crashes, we perform a conditional portfolio-level analysis of bear beta–sorted funds in market crash periods versus normal periods. We define market crashes as months during which excess market returns are lower than the sample period 10th percentile.[10] The returns of bear beta-sorted hedge fund quintiles are reported in Table 5.

[Insert Table 5 here]

As indicated in specification (1), both low and high bear beta groups of hedge funds experience significant losses when the market crashes. This is understandable because both groups have positive unhedged market exposure (see again Section 2.3). However, consistent with the idea that the market-hedged Bear factor is negative even during market crashes, insurance sellers still earn the negative premium of this factor. As a result, insurance buyers happen to underperform by an average of 2.85% per month during these periods. For example, during the October 2008 crisis, the market experienced an excess return of -17.23%, but the hedged Bear portfolio had a return of -0.80%. Accordingly, the quintile portfolio of funds with the lowest bear betas outperformed the portfolio of funds with the highest bear betas by 4.70%. During normal times as in specification (2), we still find that low bear beta funds have an average monthly return that is 0.33% higher than high bear beta funds.

[10] We obtain similar results using alternative definitions of realized market crashes, e.g., when excess market returns lower than -10%, when excess market returns lower than the sample period 5th percentile, and during the recession periods indicated by National Bureau of Economic Research (NBER).

Similarly, we examine the performance of bear beta-sorted quintiles during months when excess market returns are negative versus positive. Results from specification (3) show a significant outperformance of the most negative bear beta quintile relative to the most positive quintile when the market declines. When the market increases as in specification (4), we still find a better performance among the most negative bear beta hedge funds. However, the outperformance is not statistically significant during these months. One potential explanation for the less pronounced negative bear beta effect during periods of positive market returns is that on some occasions positive market returns are accompanied by persistently high bear market risk concerns (for example, in periods when the market rebounds) and hence coincide with periods of positive market hedged Bear factor.

Overall, our findings contradict the conventional wisdom that hedge funds acting as insurance sellers should necessarily underperform hedge funds acting as insurance buyers during market crashes. Given that both hedge fund groups have positive but nearly equal unhedged market exposure on average, they both perform poorly when market declines. The relative performance between the two groups is driven by the behaviour of the market hedged Bear portfolio.

3.2. Fund-level analysis

3.2.1. Unconditional analysis

The results from portfolio-level analysis demonstrate that a portfolio of hedge funds with low bear beta yields significantly higher expected return than the one with high bear beta. In this section, we perform Fama and MacBeth (1973) regressions that utilize the entire cross-sectional information in the data to examine whether the negative predictive power of bear beta for hedge fund returns persists after simultaneously controlling for other hedge fund characteristics. In particular, each month from January 1998 to December 2017, we perform the following cross-sectional regressions:

$$r_{i,t+1} = \psi_{0,t} + \psi_t \times \beta_{i,t}^{BEAR} + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t+1} \tag{11}$$

where $r_{i,t+1}$ is the realized return of hedge fund i in the month $t+1$, $\beta_{i,t}^{BEAR}$ is the bear beta of hedge fund i at the end of month t, and $\mathbf{Z}_{i,t}$ is a vector of fund characteristics. To distinguish the impact of bear market risk from other risk measures, we also include several hedge fund measures of risk. The details of these variables are provided in the Appendix.

Table 6 reports the time-series averages of the slope coefficients, the corresponding Newey-West adjusted t-statistics (with 24 lags), and the average adjusted R^2 from 240 monthly regressions.

[Insert Table 6 here]

The univariate regression result in specification (1) shows a negative relation between bear beta and expected hedge fund returns. The average slope, ψ_t, from the monthly regressions of hedge fund returns on bear beta is -0.59 with a t-statistic of -3.63. The economic magnitude of the bear beta effect is comparable to that shown in the univariate portfolio-level analysis. Specifically, multiplying the difference in mean values of bear beta between the high and low bear beta quintiles from Panel A of Table 3 by the slope coefficient yields a monthly risk premium differential of -0.63% between the high and low bear beta portfolio.

In specification (2), we control for fund characteristics, e.g., size, age, minimum investment amount, a fund's management and incentive fee, length of a fund's lockup and redemption period, as well as other measures of risk, e.g. past fund returns, fund return volatility, skewness, and kurtosis. We also add indicator variables that take the value of one in case the fund employs leverage, has a hurdle rate, has a high water mark, or is an offshore fund, and zero otherwise. In line with the prior literature, we find that minimum investment, past return, as well as past return volatility and skewness are positive and significant predictors of future hedge fund returns. More importantly, the association between bear beta and future hedge fund returns remains negative (coefficient=-0.35) and statistically significant (t-statistic=-3.72).

Next, we augment the above specification by including respectively in specifications (3) to (5) the exposure to market risk, higher risk-neutral market moments (Agarwal, Bakshi, and Huij, 2010), and market tail risk (Agarwal, Ruenzi, and Weigert, 2017), all computed based on an estimation window of 24 months. Depending on the specification, the average coefficient estimate on bear beta ranges from -0.25 to -0.33 with t-statistics ranging from -3.24 to -3.33. These results indicate that the above risk measures do not subsume the predictive power of bear beta for future hedge fund returns.

A potential explanation for the negative relation between bear beta and future fund returns is that low bear beta hedge fund managers have higher level of skills. In specification (6), we control for several measures of hedge fund skills, including the macroeconomic uncertainty timing skill (β^{UNC}) of Bali, Brown, and

Caglayan (2014), the skill at exploiting rare disaster concerns (β^{RIX}) of Gao, Gao and Song (2018), the R-squared measure of Titman and Tiu (2011), the strategy distinctiveness index (SDI) of Sun, Wang, and Zheng (2012), and the downside returns of Sun, Wang, and Zheng (2018). The average coefficient on bear beta is still negative and statistically significant at the 1% level, confirming the distinctive effect of bear market risk exposure.

Of primary interest is specification (7), where we control for the full set of hedge fund characteristics, exposures to other risk factors, and manager skill measures. The coefficient on bear beta remains negative, -0.29, and is significant at all conventional levels with a t-statistic of -3.05. Overall, our results document a strong negative cross-sectional relation between bear beta and future hedge fund returns. The effect is not subsumed by hedge fund characteristics, manager skills, and fund exposures to previously documented risk factors.

3.2.2. Conditional analysis

In Table 7, we investigate the association between fund-level bear beta and future hedge fund returns in different market states after controlling for a large set of fund characteristics and risk exposures. We use a specification identical to that in specification (7) of Table 6. We report the coefficients on bear beta and market beta but suppress the coefficients on other control variables for the sake of brevity.

[Insert Table 7 here]

We obtain the results that are similar to those in the conditional portfolio-level analysis. Specification (1) of Table 7 shows a strong negative relation between bear beta and hedge fund returns (coefficient of -1.15 and t-statistic of -2.75) during market crash periods, which is robust to controlling for market beta that captures funds' unhedged market exposure. During normal times, as in specification (2), we still observe a significant negative effect of fund-level bear beta and future fund returns with a bear beta coefficient equal to -0.20 and a t-statistic of -1.83. In specifications (3) and (4), we find that the relation is strongly significant during periods of negative market returns (the average bear beta coefficient of -0.67 with a t-statistic of -2.62), while it is less pronounced during periods of positive market returns (the average bear beta coefficient of -0.06 with a t-statistic of -0.42).

In contrasts, in the same regressions, we find that the impact of market beta on future hedge fund returns is significantly negative in periods of market crashes or negative market returns (specifications 1 and 3), but strongly positive during normal times or when market returns are positive (specifications 2 and 4). This opposite-sign relation is as expected: funds with higher unhedged market exposure earn premium during normal times but perform worse when tail risk realizes. Therefore, the effect of bear beta on hedge fund returns is far from fully captured by either market or realized tail risk exposure.

3.3. Increasing concern about future bear market states and bear beta effect

As low bear beta funds earn higher returns on average by being more exposed to bear market risk, we expect an opposite, i.e. positive, relation between bear beta and hedge fund returns when such risk is realized. We define increasing (decreasing) bear concern states as periods of positive (negative) market hedged Bear portfolio returns.[11] We then examine the bear beta effect conditional on these different states and report the results in Table 8.

[Insert Table 8 here]

As expected, we find that the effect of bear beta on future returns is strongly negative in periods of negative hedged Bear portfolio returns. In particular, the average coefficient on bear beta is -0.49 with a corresponding t-statistic of -3.50. However, the relation reverses and becomes positive, with an average bear beta coefficient of 0.44 and a t-statistic of 3.16, during periods of positive hedged Bear portfolio returns. These results are in line with the following economic mechanism. When the hedged Bear portfolio return is negative, the price of insurance does not increase enough to compensate for the negative market return or decreases more than what is expected given a positive market return. Therefore, hedge funds with negative bear beta (insurance sellers) outperform funds with positive bear beta (insurance buyers). Oppositely, when the hedged Bear portfolio return is positive, the insurance return exceeds in absolute terms the negative market return or decreases less than what is expected given a positive market return. Therefore, hedge funds that act as insurance buyers outperform funds that act as insurance sellers.

[11] Market hedged Bear portfolio return – the component of the Bear portfolio return that is orthogonal to market return – is equal to alpha (or intercept coefficient) plus the residual from the rolling 24-month window regressions of Bear portfolio returns on markets returns.

To better understand these results, recall from Panel B of Table 3 that return of an insurance buyer (seller) comprises a positive unhedged position and a hedged long (short) position to the market. Also, both groups have equivalent unhedged market exposure, which is around 0.43. Hence, the relative outperformance or underperformance of each hedge fund group in different periods is purely attributed to its differential exposure to the market hedged Bear factor.

4. Determinants of bear beta

To further understand which funds are more or less likely to be exposed to bear market risk, we next examine which fund characteristics and other risk measures are associated with bear beta. We perform the following regression of bear beta of hedge fund i in month t on various contemporaneous characteristics and risk measures of fund i using the Fama and MacBeth (1973) methodology:

$$\beta_{i,t}^{BEAR} = \alpha_t + \phi_t' \mathbf{Z}_{i,t} + \varepsilon_{i,t}, \qquad (12)$$

where $\beta_{i,t}^{BEAR}$ is the bear beta of hedge fund i in the month t, and $\mathbf{Z}_{i,t}$ is a vector of fund characteristics. Table 9 reports the time-series averages of the slope coefficients and the corresponding Newey-West adjusted t-statistics (with 24 lags).

[Insert Table 9 here]

Column (1) investigates the association between bear beta and time-varying fund characteristics such as fund size, age, return volatility, skewness, kurtosis and past yearly return. We find that hedge funds with low bear betas tend to be younger. Intuitively, young funds probably have incentives to attract fund flows by establishing a track record of high returns early in their life cycle. Thus, these funds are more likely to get involved in selling bear market insurance since it offers high compensation. Furthermore, consistent with risk-inducing behavior, there is a positive relation between fund bear beta and return skewness. Equivalently, insurance sellers, which are exposed to bear market risk, exhibit left-skewed return distributions. However, despite having more negative return skewness, these funds have higher past-year returns.

In column (2), we include time-invariant contractual features such as fund's minimum investment amount, management and incentive fees, lockup and redemption periods, as well as indicator variables that equal one if a given fund is offshore, employs leverage, has a high-water mark and a hurdle rate. Intuitively, hedge funds with low bear betas are associated with measures of managerial incentives such as high management fees, existence of a hurdle rate, and offshore location. There is a positive relation between fund bear beta and incentive fee, but this finding is consistent with Agarwal, Daniel, and Naik (2009) who find that incentive fees do not capture managerial incentives as two managers charging the same incentive fee can face different dollar incentives. We find a mixed relation between fund bear beta and managerial discretion. Specifically, funds with low bear betas have longer redemption periods and are probably more flexible to take on riskier positions, but are less likely to employ leverage. Intuitively, hedge funds that employ leverage tend to act more as insurance buyers, probably because their trading profile is already quite risky. In contrast, unlevered hedge funds tend to act more as insurance sellers probably because they find alternative ways to boost their returns rather than employing leverage.

In column (3), we include all fund characteristics and contractual features together in the same regression model. Although, the statistical significance of some of the variables is reduced, the main findings about the determinants of bear beta remain intact.

5. Further analysis

5.1. Bear beta and manager skills at exploiting rare disaster concerns

In a related study, Gao, Gao and Song (2018) also use a positioning in put options (see their Equation (4)) in order to capture investors' perceptions about market-wide tail risk and show that hedge funds with high sensitivity to rare disaster concern index (RIX) earn on average higher returns than hedge funds with low sensitivity to the RIX index. Their put portfolio is more complicated and is designed to capture extreme negative price movements. In contrast, the Bear portfolio is simpler, and the level of extreme returns captured can be easily adjusted. Despite this difference, the two put option portfolios are conceptually similar. Therefore, it is important to understand why the results of our paper are different from theirs.

Gao, Gao and Song's (2018) RIX index is the *average daily price within a month* of a portfolio of put options on various indices from sectors including banking, semiconductor, precious metals, housing, oil service, and utilities. Hedge funds' sensitivity to this measure (β^{RIX}) is interpreted as skill of exploiting the market's ex ante rare disaster concerns.[12] In contrast, the Bear factor is the *monthly return* of a portfolio of put options. As a result, it captures the return of an insurance contract against concerns about future bear market states. Our conjecture is that the difference in the results of the two papers comes from the different approaches in using average prices within the month versus monthly returns and not from the different portfolio of puts that is used in each paper. This implies that if we use the return – rather than the price – of the portfolio of put options that form the RIX index, we will get a predictive pattern that resembles the one presented in this paper.

[Insert Table 10 here]

Panel A of Table 10 presents the results from a portfolio sorting exercise based on hedge fund sensitivity to various versions of the RIX index. For consistency with Gao, Gao and Song's (2018) study, all the results span the period from January 1998 to December 2011 and are based on decile portfolios. Model (1) uses the RIX index that is made publicly available by George Gao and covers the period 1996-2011. We observe a pattern that is very close to what is reported in Gao, Gao and Song (2018). Model (2) presents the result of the same analysis but with our replication of the RIX index. Our RIX index has a 99% correlation with the RIX index provided by Gao and hence, as expected, the results are very close to Model (1). Model (3) shows the results using a RIX index constructed using only S&P500 index options – rather than using a mixture of six indices as in the main RIX. Similar to Gao, Gao, and Song (2018) (see their Internet Appendix), we find a positive albeit less significant association between the sensitivity to this RIX index and hedge fund returns. Overall, high RIX beta funds, on average, outperform low RIX beta funds and they are able to avoid significant losses when market crashes occur. According to Gao, Gao, and Song (2018), this is because these high RIX beta funds skillfully time the selling of overpriced crash insurance.

Models (4) in Panel A of Table 10 show the main result of this section. We construct an investable disaster concern factor from a portfolio of S&P500 put options as in Equation (4) in Gao, Gao and Song (2018). The factor captures the return of the put option portfolio, rather than the average daily price within the month. The option positions are formed on a daily basis, and the daily returns within the month are averaged to create the monthly RETRIX. Construction of this investable factor is detailed in the Appendix. We argue

[12] Gao, Gao and Song's (2018) finding does not point to a risk-based explanation. RIX is persistent with an autocorrelation coefficient of 0.92, which is not a risk factor per se as the innovations in concerns about future bear market states.

that the covariance between hedge fund returns and the returns, rather than the contemporaneous price levels, of a portfolio of put options provides a more intuitive way to classify hedge funds as insurance buyers or sellers. Now, we observe that the pattern is reversed and there is a negative and significant association between sensitivity to RETRIX (β^{RETRIX}) and future hedge fund returns. Furthermore, in line with our main empirical evidence, insurance sellers still outperform insurance buyers during periods of market crashes. However, this is not because these insurance sellers have higher skills, but because they are mechanically more exposed to bear market risk.

It is straightforward to ask whether β^{RETRIX} absorbs the positive effect of β^{RIX} on future hedge fund returns. To answer this question, we report in Panel B of Table 10 two sets of bivariate dependent sorts according to β^{RETRIX} and β^{RIX}. In Panel B.1, we first sort all hedge funds into quintiles based on their RETRIX betas, and then within each RETRIX beta quintile, we further sort funds into five portfolios based on their RIX betas. We observe the outperformance of high RIX beta funds relative to low RIX beta funds in all RETRIX beta quintiles, even in the high RETRIX beta group that is classified as buying insurance. Possibly, RIX beta reflects a skillful timing of selling crash insurance rather than a blind selling of it, thus containing a different information from the exposure to bear market risk. In Panel B.2, when we first sort hedge funds based on RIX betas into quintiles and then sorts funds within each RIX beta quintile into five RETRIX beta portfolios, we still observe the outperformance of low RETRIX beta funds relative to high RETRIX beta funds within each RIX beta quintile. The risk-adjusted return spreads of high-minus-low RETRIX beta portfolios range from -0.33% to -0.83% per month, all statistically significant at 5% level.

Overall, the results of this section show that the exact portfolio of put options that is used to capture negative market movements is of secondary importance for analyzing the cross-section of hedge fund returns. What is of primary importance is whether we consider the average price of this portfolio (the sensitivity to which reflects skill according to Gao, Gao, and Song; 2018) or the return of this portfolio (the sensitivity to which reveals whether a hedge fund acts more as an insurance buyer or seller).

5.2. Bear market risk and future hedge fund returns conditional on investment styles

To provide some insights as to whether the predictive power of bear beta for future hedge fund returns is an inter- versus intra-style effect, we examine the performance (returns and alphas) of bear beta sorted portfolios separately using funds within each investment style. Table 11 presents the results.

[Insert Table 11 here]

We exclude the short-bias category because, as shown in Table 1, we do not have enough observations to perform a meaningful analysis. Table 11 shows that there is a high variation in bear betas within each hedge fund investment style. Consistent with this finding, we further observe a strong and negative relation between bear beta and portfolio returns in all the nine investment styles. Among the most significant styles, return spreads between high and low bear beta quintiles are -0.72% per month for relative-value, -0.70% for global macro, and -0.61% for multi-strategy. The corresponding alpha differentials are also economically substantial and statistically significant. The return and associated alpha spreads are lower among equity market neutral, fund of funds and long-short equity funds, but they are all statistically significant. In summary, there is a high variation in the exposure to bear market risk within each investment style and hedge funds seem to exhibit both inter- and intra-style bear market risk pricing.

5.3. Bear market risk and long-term future hedge fund returns

We further investigate how strong bear beta is in terms of predicting long-term future hedge fund returns. From a practical point of view, this is important because some investors and hedge fund managers might be more interested in long investment horizons. In fact, the lock-up periods for hedge fund managers can be sometimes up to one year.

[Insert Table 12 here]

First, we perform a univariate portfolio analysis, similar to that presented in Table 4, but we focus on the predictability of the return of month $t + k$ – with k ranging from two to nine – rather than the return of month $t + 1$. Panel A of Table 12 presents the results. As expected, the magnitude of the return differentials (in absolute terms) becomes smaller as the gap between the month bear beta-sorted portfolios are generated and the month the performance of those portfolios is evaluated increases. However, the return and alpha spreads are all negative and statistically significant up to the eighth month. In the ninth month, the alpha spread is still negative, but not significant at the 5% level. Overall, bear beta is a persistent predictor of future hedge fund returns since its predictive power lasts for up to eight months ahead.

Next, we examine the returns of bear beta portfolios by holding them for long-term horizons ranging from three months to 24 months. We follow Jegadeesh and Titman (1993) and implement the independently managed portfolio strategy to address the returns from overlapped holding periods. Panel B of Table 12 reveals a significant performance persistence for up to 24 months ahead, with return differences between high and low bear beta funds of -0.58%, -0.49%, -0.30%, and -0.18% per month for a holding horizon of three, six, twelve, and twenty-four months, respectively. Moreover, these return differences are statistically significant at the 5% level, showing that bear beta can successfully predict long-horizon cumulative hedge fund returns for up to 24 months into the future.

Fund returns are often reported with a lag and it takes some time to start an investment into a hedge fund. Considering this practical issue in investing in hedge funds, we implement a portfolio strategy that is identical to that in Panel B except that we now leave a one-month gap between the portfolio formation month and the month in which portfolio returns start being calculated. The results reported in Panel C of Table 12 are similar to those presented in Panel B. In particular, we still observe a significant outperformance of low bear beta funds compared to high bear beta funds even when considering an 18-month holding period.

6. Robustness checks

In this section, we further corroborate our findings in the paper by conducting a battery of robustness checks on the predictive power of bear beta for one-month ahead hedge fund returns based on portfolio-level analysis.

[Insert Table 13 here]

First, instead of equal-weighted returns as in our baseline analysis, we use value-weighted returns. Specification (1) of Table 13 shows that the bear beta effect is both statistically and economically significant when portfolio returns are weighted by asset under management too. For example, the underperformance of hedge funds in the highest bear beta, compared to the lowest bear beta, quintile is economically large, generating an average return spread of -0.63% per month with a t-statistic of -3.42. The associated alpha difference between these two quintiles is -0.73% per month and also statistically significant.

Second, we examine the stability of our results by changing the bear beta estimation horizon from 24 months to either 12 or 36 months. As shown in specifications (2) and (3) of Table 13, the Q5-Q1 portfolio return spread is -0.50% and -0.42% per month for a bear beta estimation horizon of 12 months and 36 months, respectively. The corresponding t-statistics are -2.75 and -4.30. The risk-adjusted returns of the Q5-Q1 bear beta portfolio based on the Fung and Hsieh (2004) seven factor model are also negative and statistically significant at the 1% level in both specifications.

Third, we investigate whether our results are robust to alternative definitions of the Bear portfolio. In specifications (4) and (5) of Table 13, we define bear region as states in which the market excess return is one or two standard deviations, instead of 1.5 standard deviations, below zero. We still find significantly negative return and Fung-Hsieh alpha differences between the portfolio of high $\beta_{1\sigma}^{Bear}$ (or $\beta_{2\sigma}^{Bear}$) hedge funds and the portfolio of low $\beta_{1\sigma}^{Bear}$ (or $\beta_{2\sigma}^{Bear}$) hedge funds. Next, we use only the long put position by dropping the short put position from the Bear portfolio. This put portfolio is simpler and conceptually closer to the portfolio utilized by Agarwal and Naik (2004). As shown in specification (6) of Table 13, the portfolio of low β^{PUT} hedge funds outperforms the portfolio of high β^{PUT} hedge funds with significant return and alpha differences. In an unreported analysis, we also find that funds with low β^{PUT} still outperform funds with high β^{PUT} during periods of market crashes.

Finally, as a way to mitigate survivorship bias, in specification (7) of Table 13 we repeat the baseline analysis by assuming that returns of the drop-out funds are -100% in the month following the last reporting month. This is because the HFR database does not report delisting hedge fund returns. This delisting return assumption does not change our conclusion. For instance, the return and alpha spreads between Q5 and Q1 are -0.80% (t-statistic of -4.41) and -0.93% (t-statistic of -4.46), respectively. Besides, our results are not materially affected when we assign different value for delisted hedge fund returns, such as -75%, -50%, -25%, and zero.

7. Conclusion

It is well documented that hedge funds, at an aggregate level, are exposed to tail risk by following trading strategies similar to providing insurance, i.e. writing a put option on the market index. However, the literature has paid little attention to the return behavior of insurance sellers, relative to insurance buyers, in the cross-section. In this paper, we use the bear beta, i.e. the sensitivity of each hedge fund to a market hedged Bear portfolio, to classify hedge funds as insurance sellers or buyers and examine its predictive power for the cross-section of fund returns.

The returns of the market hedged Bear portfolio reflect changes in bear market concerns after accounting for the strong negative relation between the Bear portfolio and the market. We show that, despite this strong negative relation, the market and the Bear portfolio do not move in lockstep. Therefore, the relative price movement between the two is a proxy for the innovation in bear market risk. In fact, we find that when we take into consideration the hedge funds' insurance-related positions, the unhedged market exposure of insurance buyers and insurance sellers is almost identical. Therefore, any differences in their expected returns should be naturally attributed to their differential exposure to bear market risk, captured by bear beta.

In a portfolio-level analysis, funds in the lowest bear beta quintile (insurance sellers) outperform funds in the highest bear beta quintile (insurance buyers) by 0.58% per month an average. The risk-adjusted return difference between these two quintiles remains economically large and statistically significant. Results from multivariate regressions reveal a negative and statistically significant effect of bear beta on future fund returns after controlling for a large set of fund characteristics and risk attributes. Therefore, the explanatory power of bear beta is distinct from previously documented hedge fund return predictors.

Our interpretation for the above findings is that insurance sellers earn high returns on average by harvesting the bear market risk premium, while insurance buyers earn low returns on average because they willingly pay this insurance premium. Consistent with our risk-based explanation, the relation between bear beta and future fund returns is reversed and becomes positive during months of positive market hedged Bear portfolio returns. In contrast, it remains negative in the rest of the periods, and especially in periods of negative market returns or market crashes. Overall, our paper provides evidence that bear market risk is a distinctive concept and not always closely associated with realized market tail risk.

Appendix A: Definition of variables

For each stock i at the end of month t, we compute all variables used to predict fund returns in month $t+1$. This appendix provides detailed definition of all variables in the paper. Note that for all variables computed using the past 24 months of hedge fund return series, we require at least 18 months of non-missing returns.

A.1. Time-varying fund exposures and characteristics

$\boldsymbol{\beta^{BEAR}}$ ***or Bear Beta*****:** is the coefficient $\beta_{i,t}^{BEAR}$ obtained by regressing monthly hedge fund excess returns on excess market returns and Bear portfolio excess returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t} \times MKT_t + \beta_{i,t}^{BEAR} \times r_{Bear,t} + \epsilon_{i,t}$ over a 24-month rolling-window period. Details of Bear portfolio construction is provided in Section 2.

$\boldsymbol{\beta^{MKT}}$: is the coefficient $\beta_{i,t}^{MKT}$ from the regression of monthly excess fund returns on excess market returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \epsilon_{i,t}$ over the past 24 months.

$\boldsymbol{\beta^{\Delta VOL}}$***,*** $\boldsymbol{\beta^{\Delta SKEW}}$***, and*** $\boldsymbol{\beta^{\Delta KURT}}$*(Agarwal, Bakshi, and Huij, 2009)*: are exposures to higher risk-neutral moments obtained by regressing monthly excess fund returns on excess market returns and ΔVOL_t, $\Delta SKEW_t$, and $\Delta KURT_t$ (monthly relative changes in the market volatility, skewness, and kurtosis respectively) over a 24-month rolling-window period: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{\Delta VOL} \times \Delta VOL_t + \beta_{i,t}^{\Delta SKEW} \times \Delta SKEW_t + \beta_{i,t}^{\Delta KURT} \times \Delta KURT_t + \epsilon_{i,t}$, with a requirement of at least 18 months of fund return data. Market volatility, skewness, and kurtosis are the Bakshi, Kapadia, and Madan (2003) model-free estimate of risk-neutral higher moments of market log return spanning the period up to option maturity day. They are extracted from S&P 500 Index options using trapezoidal approximation and are linearly interpolated to have the measures with constant 30-day maturity.

TailRisk *(Agarwal, Ruenzi, and Weigert, 2017)*: is defined as the lower tail dependence of hedge fund returns and the market returns over the past 24 months ($TailSens_{i,t}$), multiplied by the ratio of the absolute value of their respective expected shortfalls over the same period with the cutoff of q = 5%. $TailSens_{i,t}$ of fund i takes the value of zero, 0.5, or 1 if none, one, or both of the fund's two worst return realizations occur at the same time of the market's two worst monthly returns over the past 24 months.

$\boldsymbol{\beta^{UNC}}$ *(Bali, Brown, and Caglayan, 2014)*: is hedge fund exposure to macroeconomic uncertainty, $\beta_{i,t}^{UNC}$, from the regression of monthly excess hedge fund returns on economic uncertainty index: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNC} \times UNC_t + \epsilon_{i,t}$ over the past 24 months. The monthly economic uncertainty index is provided on Bali's personal website.

$\boldsymbol{\beta^{RIX}}$ *(Gao, Gao, and Song, 2018)*: is interpreted as skills at exploiting rare disaster concern, which is the coefficient, $\beta_{i,t}^{RIX}$, from the regression of monthly hedge fund returns on excess market return and rare disaster concern index (RIX) over the past 24-month window: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{RIX} \times RIX_t + \epsilon_{i,t}$. Data for RIX is obtained from Gao's website and covers the period over 1996-2011.

$\boldsymbol{\beta^{RETRIX}}$: is the coefficient on *RETRIX* obtained by regressing monthly hedge fund returns on excess market return and Investable RIX factor over the rolling 24-month window period: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{RETRIX} \times RETRIX_t + \epsilon_{i,t}$. Monthly investable RIX factor is computed as follows. We modify the formula for RIX slightly to allow the use of available option quotes.

$$RIX = V^- - IV^- = \frac{2e^{r\tau}}{\tau} \int_{K<S_t}^{\cdot} \frac{\ln(S_t/K)}{K^2} \; P(S_t; K, T) dK$$

$$\approx \frac{2e^{r\tau}}{\tau} \sum_{i=1}^{n_P} \frac{ln\left(S_t/K_i^P\right)}{\left(K_i^P\right)^2} P\left(S_t; K_i^P, T\right) \Delta K_i^P$$

where $\tau \equiv T - t$ is the time to maturity, r is the risk-free rate, S_t is the spot price, n_P is the number of OTM puts with available price data, i indexes the OTM puts, K_i^P is the strike of ith OTM put option when the strikes are ordered in decreasing order, and $P\left(S_t; K_i^P, T\right)$ is price of the put with strike K_i^P maturing at T. $\Delta K_1^P = S - K_1^P$ and $\Delta K_i^P = K_{i-1}^P - K_i^P$ for $2 \leq i \leq n^P$. For constructing RETRIX, each day, we follow the formula to form the option position using all valid OTM put options on the S&P500 index that expire on the third Friday of the next calendar month. The option position is hold for one day to calculate the return. We then take the average of the daily option position returns within a month to calculate monthly *RETRIX*.

$\boldsymbol{R2}$ *(Titman and Tiu, 2011)*: is the R^2 measure of a fund from the regression of monthly hedge fund returns on Fung and Hsieh (2004) seven-factor model over the past 24-month period.

SDI *(Sun, Wang, and Zheng, 2012)*: is strategy distinctiveness for a fund calculated as one minus the correlation between the fund returns and the average returns of funds with the same investment style based on the past 24 months.

Downside Return *(Sun, Wang, and Zheng, 2018)*: is computed as the time-series average of fund i returns during months in which aggregate hedge funds returns are below the median level over the past 24-month window.

Age: is he age of a hedge fund i since its inception (measured in years)

Size: is computed as natural log of asset under management (in $ million) of hedge fund i at the ned of month t.

Ret VOL, SKEW, KURT: are respectively the standard deviation, skewness, and kurtosis of fund i monthly returns over the past 24 months.

Past return (12M): is the cumulative returns of fund i over the past 12 months ending in month t.

A.2. Time-invariant fund characteristics

Min Investment: is computed as the natural log of (1 + minimum investment amount).

Management Fee: is the annual management fee (in percentage) for hedge fund i.

Incentive Fee: is the annual incentive fee (in percentage) for hedge fund i.

Lockup: is the minimum length of time (measured in months) that investors are required to keep their money invested in fund i.

Redemption: is the length of advanced notice that hedge fund i requires from investors who wish to redeem their shares.

Leverage: is an indicator variable that takes the value of one if hedge fund i uses leverage or zero otherwise.

Hurdle: is an indicator variable that takes the value of one if hedge fund i uses a hurdle rate or zero otherwise.

High Water Mark: is an indicator variable that takes the value of one if hedge fund i use high watermark or zero otherwise.

Offshore: is an indicator variable that takes the value of one if hedge fund i is based in offshore location outside of the USA or zero otherwise.

A.3. Hedge fund risk factors

PTFSBD: Monthly return on trend-following risk factor in bonds

PTFSFX: Monthly return on trend-following risk factor in currencies.

PTFSCOM: Monthly return on trend-following risk factor in commodities.

S&P: The S&P 500 index monthly total return.

SCMLC: The size spread factor, computed as the difference between the Russell 2000 index monthly return and the S&P 500 monthly return.

BD10RET: The bond market factor, computed as the monthly change in the 10-year treasury maturity yield.

BAAMTSY: The credit spread factor, computed as the monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield.

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Figure 1: Time-series of market hedged Bear factor

The figure plots the monthly time-series of the market hedged Bear portfolio excess returns over January 1998 to December 2017. Market hedged Bear portfolio excess return in month t is equal to the intercept coefficient plus the month t residual from a regression of the Bear portfolio excess returns on the market excess returns over the past 24 months. Bear portfolio excess return (Bear factor) is the one-month buy-and-hold excess return of a bear spread portfolio that longs an OTM put and shorts a further OTM put on the S&P500 index.

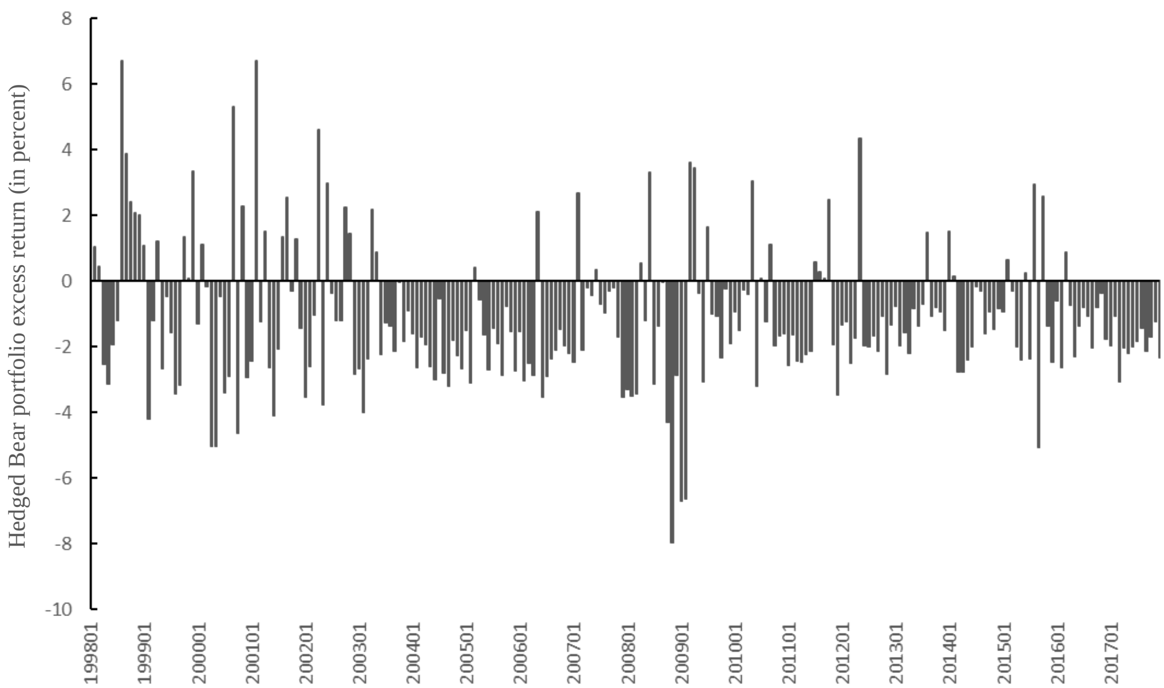

Table 1: Descriptive statistics of hedge funds

The table presents summary statistics for the hedge funds used in our sample. Panel A shows the time-series average of the monthly cross-sectional mean, standard deviation, and percentiles for the returns (in percent) of hedge funds in each investment style category and in total. N is the number of distinct hedge funds in each category. Panel B reports the number of hedge funds and the total asset under management (in $ billions) each year for all hedge funds in our sample, as well as the mean, median, standard deviation, minimum and maximum monthly returns (in percent) of the respective equal-weighted hedge fund portfolio. Panel C presents cross-sectional mean and distribution statistics for hedge fund characteristics including size, age, management fee, incentive fee, redemption notice period, lockup period, and minimum investment amount for all hedge funds in our sample. Our sample covers hedge funds from the HFR database over the period January 1996 to December 2017.

Panel A: Summary statistics of hedge fund returns (in percent) by categories

	N (Funds)	Mean	STD	P10	P25	P50	P75	P90
Event Driven	832	0.70	3.22	-1.86	-0.48	0.61	1.74	3.27
Relative Value	1366	0.62	2.74	-1.54	-0.26	0.64	1.56	2.84
Long-Short Equity	2936	0.78	4.73	-3.93	-1.46	0.70	2.91	5.51
Global Macro	443	0.64	4.39	-3.71	-1.31	0.54	2.47	5.08
CTA	422	0.45	4.20	-3.67	-1.30	0.33	2.05	4.64
Equity Market-Neutral	549	0.42	2.30	-2.08	-0.76	0.42	1.57	2.95
Multi-Strategy	1715	0.65	4.07	-3.32	-1.17	0.58	2.37	4.63
Short-Bias	60	-0.15	3.55	-4.50	-2.45	-0.19	2.11	4.30
Sector	505	0.97	5.20	-4.56	-1.74	0.90	3.48	6.56
Fund of Funds	2256	0.50	1.86	-1.17	-0.26	0.50	1.26	2.14
All hedge funds	11084	0.64	4.03	-2.93	-0.83	0.55	2.01	4.24

Panel B: Summary statistics year by year

Year	Start	Entries	Dissolved	End	AUM ($B)	Equal-weighted hedge fund portfolio monthly returns (%)				
						Mean	Median	STD	Min	Max
1996	764	185	40	909	108.6	1.43	1.63	1.59	-2.00	3.87
1997	909	365	63	1211	170.2	1.34	1.29	2.01	-1.39	4.57
1998	1211	319	149	1381	169.4	0.22	0.26	2.62	-6.38	3.20
1999	1381	349	139	1591	212.1	2.13	1.20	2.32	-0.45	6.84
2000	1591	402	163	1830	255.4	0.70	0.18	2.49	-2.49	5.60
2001	1830	418	183	2065	319.0	0.46	0.71	1.43	-2.20	2.72
2002	2065	501	138	2428	376.2	0.11	0.35	1.06	-1.93	1.63
2003	2428	669	209	2888	558.6	1.37	1.11	0.98	-0.20	3.49
2004	2888	744	203	3429	809.9	0.67	0.72	1.23	-1.41	2.90
2005	3429	824	299	3954	939.7	0.67	1.23	1.32	-1.58	1.96
2006	3954	800	415	4339	1211.9	0.97	1.30	1.34	-1.55	3.17
2007	4339	725	481	4583	1549.3	0.88	0.84	1.47	-1.68	2.93
2008	4583	557	875	4265	1095.6	-1.69	-1.74	2.78	-6.71	1.87
2009	4265	414	739	3940	1010.6	1.55	1.44	1.64	-1.10	4.87
2010	3940	470	483	3927	1119.9	0.83	1.00	1.77	-2.85	3.29
2011	3927	415	502	3840	1104.9	-0.36	-0.10	1.75	-3.54	2.40
2012	3840	388	573	3655	1101.2	0.56	0.68	1.24	-2.19	2.56
2013	3655	338	451	3542	1237.9	0.83	1.13	1.07	-1.45	2.54
2014	3542	337	381	3498	1298.0	0.31	-0.24	0.94	-0.74	1.93
2015	3498	245	469	3274	1280.8	-0.07	0.15	1.28	-2.30	1.93
2016	3274	222	424	3072	1178.4	0.42	0.56	1.18	-2.58	1.93
2017	3072	201	379	2894	1211.1	0.73	0.60	0.36	0.19	1.16

Panel C: Summary statistics of hedge fund characteristics

	N	Mean	STD	P10	P25	P50	P75	P90
Average monthly AUM ($M)	11084	171.19	601.42	11.56	20.96	49.30	137.17	363.05
Average age of fund (in months)	11084	78.33	63.95	16.27	31.96	60.00	107.01	167.07
Management fee (%)	11084	1.44	0.57	1.00	1.00	1.50	2.00	2.00
Incentive fee (%)	11084	15.78	7.54	0.00	10.00	20.00	20.00	20.00
Redemption (in months)	11084	1.24	1.10	0.03	0.33	1.00	2.00	3.00
Lockup (in months)	11084	3.46	6.92	0.00	0.00	0.00	6.00	12.00
Minimum Investment ($M)	11084	1.26	4.63	0.05	0.10	0.50	1.00	2.00

Table 2: Descriptive statistics for Bear portfolio and factor analysis of its returns

The table reports summary statistics and factor analysis results for the Bear factor. Bear factor is the one-month buy-and-hold excess return of a bear spread portfolio that longs an OTM put and shorts a further OTM put on the S&P500 index. Panel A presents the mean (Mean), standard deviation (STD), skewness (Skew), minimum value (Min), 10^{th} percentile value (P10), 50^{th} percentile value (P50), 90^{th} percentile value (P90), and maximum value (Max) for the monthly time-series of the Bear factor from January 1996 to December 2017. Panel B shows the results from time-series regressions of the Bear factor on standard risk factors in the asset pricing and hedge fund literature over 264 months from January 1996 to December 2017. The table includes alphas (or intercept coefficients), slope coefficients, and adjusted R^2s. MKT, SMB, and HML represent the Fama and French (1993) factors. UMD represents the Carhart (1997) momentum factor. PTFSBD, PTFSFX, PTFSCOM, S&P, SCMLC, BD10RET, and BAAMTSY represent the Fung and Hsieh (2004) seven factors and are detailed in Appendix A. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

Panel A: Summary statistics of the monthly Bear portfolio excess returns (in percent)

Factor	Mean	STD	Skew	Min	P10	P50	P90	Max
Bear	-1.64	4.41	2.64	-5.18	-4.71	-3.27	4.10	27.55

Panel B: Factor analysis of the Bear portfolio excess returns

	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	-1.64	-1.09	-1.12	-1.11	-0.89	-0.91
	(-5.04)	(-6.77)	(-6.66)	(-6.59)	(-5.13)	(-5.57)
MKT		-0.85	-0.86	-0.86		
		(-15.90)	(-17.40)	(-16.09)		
SMB			0.09	0.10		
			(3.22)	(3.15)		
HML			0.09	0.08		0.14
			(1.26)	(1.32)		(3.08)
UMD				-0.01		-0.02
				(-0.18)		(-0.59)
PTFSBD					0.04	0.04
					(1.80)	(1.92)
PTFSFX					0.01	0.00
					(0.81)	(0.58)
PTFSCOM					-0.01	0.00
					(-0.78)	(-0.36)
S&P					-0.80	-0.80
					(-12.41)	(-15.23)
SCMLC					-0.05	-0.04
					(-1.48)	(-1.34)
BD10RET					0.01	0.01
					(1.22)	(1.05)
BAAMTSY					0.02	0.02
					(3.26)	(3.69)
Adjusted R^2	0.00	0.72	0.72	0.72	0.73	0.74

Table 3: Bear beta quintile portfolios and market exposure

The table reports the average bear beta and market exposure based on different regression models for each bear beta quintile portfolio. Bear beta (β^{BEAR}) is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) bear betas. For each quintile, we report the time-series average of other regression coefficients. In Panel A, β^{M} is the coefficient $\beta_{i,t}^{M}$ from the regression of monthly hedge fund excess returns on market excess returns and bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$ over the past 24 months. In Panel B, β^{MKT} and β^{HEDGED_BEAR} are respectively the coefficients $\beta_{i,t}^{MKT}$ and $\beta_{i,t}^{HEDGED\_BEAR}$ from the regression of monthly hedge fund excess returns on market excess returns and market-hedged bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{HEDGED\_BEAR} \times r_{HEDGED\_BEAR,t} + \epsilon_{i,t}$ over the past 24 months, where market-hedged bear factor returns are estimated as residuals from the regression of bear factor returns on market excess returns over the past 24 months. In Panel C, $\beta^{UNHEDGED\_BEAR}$ is the coefficient $\beta_{i,t}^{UNHEDGED\_BEAR}$ from the regression of monthly hedge fund excess returns on bear factor returns: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNHEDGED\_BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$ over the past 24 months. We also report the results for the Q5-Q1 portfolio. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

Panel A: Regression model $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \times MKT_t + \beta_{i,t}^{BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$

Sort by β^{BEAR}	Q1	Q2	Q3	Q4	Q5	Q5-Q1	t-stat (Q5-Q1)
β^{M}	-0.04	0.15	0.22	0.36	0.89	0.93	(10.54)
β^{BEAR}	-0.55	-0.14	-0.03	0.10	0.53	1.08	(13.55)

Panel B: Regression model $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT} \times MKT_t + \beta_{i,t}^{HEDGED\_BEAR} \times r_{HEDGED\_BEAR,t} + \epsilon_{i,t}$

Sort by β^{BEAR}	Q1	Q2	Q3	Q4	Q5	Q5-Q1	t-stat (Q5-Q1)
β^{MKT}	0.43	0.27	0.24	0.28	0.43	0.01	(0.1)
β^{HEDGED_BEAR}	-0.55	-0.14	-0.03	0.10	0.53	1.08	(13.55)

Panel C: Regression model $r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{UNHEDGED\_BEAR} \times r_{BEAR,t} + \epsilon_{i,t}$

Sort by β^{BEAR}	Q1	Q2	Q3	Q4	Q5	Q5-Q1	t-stat (Q5-Q1)
$\beta^{UNHEDGED\_BEAR}$	-0.51	-0.28	-0.22	-0.22	-0.27	0.24	(4.63)

Table 4: Performance of bear beta-sorted hedge fund portfolios

The table reports the results from the analysis of bear beta-sorted hedge fund portfolios. Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. Panel A presents the average returns and Fung-Hsieh alphas (in monthly percentages) of hedge fund portfolios sorted with respect to bear beta. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) bear betas. We hold these quintile portfolios for one month and present the average equal-weighted returns and alphas for each quintile and for the Q5-Q1 portfolio. Panel B presents alphas (or intercept coefficients) and slope coefficients from time-series regressions of the monthly equal-weighted Q5-Q1 bear beta portfolio returns on different risk factors. As standard risk factors, we use the seven factors from the Fung and Hsieh (2004) model, which include three trend-following risk factors (PTFSBD, PTFSFX, PTFSCOM), two equity-oriented risk factors (S&P, SCMLC), and two bond-oriented risk factors (BD10RET, BAAMTSY). In addition to the Fung and Hsieh (2004) seven factors, we use the Fama and French (1993) value factor (HML), the Carhart (1997) momentum factor (UMD), the Pastor and Stambaugh (2003) liquidity factor (PS LIQ), and returns of a long-short hedge fund portfolio with regard to the Bali, Brown, and Caglayan (2014) macroeconomic uncertainty factor (Return Macro), the Agarwal, Bakshi, and Huij (2010) relative change in risk-neutral volatility and skewness (Return VOL and Return SKEW), the Gao, Gao, and Song (2018) RIX factor (Return RIX), and the Agarwal, Ruenzi, and Weigert (2017) tail risk factor (Return TailRisk). Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

Panel A: Univariate portfolio sorts

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Equal-weighted returns (%)	0.87	0.56	0.47	0.44	0.29	-0.58
	(5.44)	(5.00)	(3.93)	(3.27)	(1.61)	(-3.53)
FH alpha	0.70	0.40	0.30	0.23	-0.02	-0.72
	(4.04)	(3.94)	(3.21)	(2.38)	(-0.17)	(-3.73)

Panel B: Alphas after controlling additional factors

	(1) Q5-Q1	(2) Q5-Q1	(3) Q5-Q1	(4) Q5-Q1	(5) Q5-Q1	(6) Q5-Q1	(7) Q5-Q1	(8) Q5-Q1
Alpha	-0.72	-0.69	-0.67	-0.59	-0.57	-0.61	-0.71	-0.49
	(-3.73)	(-3.34)	(-2.93)	(-4.04)	(-3.63)	(-3.12)	(-3.57)	(-3.38)
PTFSBD	-0.02	-0.02	-0.02	-0.03	-0.03	-0.02	-0.02	-0.03
	(-1.00)	(-1.20)	(-1.24)	(-1.62)	(-1.64)	(-1.03)	(-1.37)	(-1.85)
PTFSFX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(-0.29)	(-0.08)	(-0.05)	(-0.16)	(-0.19)	(0.11)	(-0.24)	(-0.20)
PTFSCOM	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.00
	(1.15)	(1.00)	(1.01)	(0.90)	(0.34)	(1.10)	(0.53)	(0.05)
S&P	0.13	0.11	0.11	0.11	0.08	0.09	0.27	0.19
	(1.51)	(1.41)	(1.34)	(1.53)	(1.48)	(1.01)	(1.52)	(1.51)
SCMLC	0.12	0.12	0.12	0.14	0.03	0.13	0.18	0.10
	(1.55)	(1.94)	(2.00)	(2.12)	(0.84)	(2.28)	(1.86)	(2.14)
BD10RET	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00
	(0.70)	(0.83)	(0.82)	(1.68)	(-0.08)	(1.27)	(0.68)	(0.52)
BAAMTSY	0.00	0.00	0.01	0.01	0.00	0.01	-0.01	0.00
	(0.40)	(0.43)	(0.52)	(0.88)	(-0.16)	(1.87)	(-0.80)	(-0.26)
HML		-0.16	-0.16	-0.14	-0.05	-0.16	-0.25	-0.11
		(-3.20)	(-3.32)	(-2.46)	(-1.62)	(-2.85)	(-2.23)	(-2.09)
UMD		-0.01	-0.01	0.01	-0.02	-0.01	-0.03	-0.03
		(-0.25)	(-0.30)	(0.17)	(-0.51)	(-0.28)	(-0.74)	(-0.73)
PS LIQ			0.01					(0.00
			(0.40)					(-0.08)
Return Macro				-0.19				-0.09
				(-2.91)				(-1.33)
Return VOL					0.50			0.44
					(3.16)			(2.90)
Return SKEW					0.31			0.27
					(3.25)			(2.38)
Return RIX						-0.23		-0.17
						(-1.47)		(-1.15)
Return TailRisk							-0.26	-0.20
							(-1.22)	(-1.87)
Adjusted R^2	0.12	0.17	0.17	0.25	0.41	0.20	0.22	0.47
Observations	240	240	240	240	240	240	240	240

Table 5: Performance of bear beta-sorted hedge fund portfolios conditional on different market states

The table reports the average equal-weighted excess returns of hedge fund portfolios sorted with respect to bear beta during periods of market crashes versus normal times. MKT denotes the excess return of the market. In specification (1), we define the periods of market crashes as months when excess market returns are lower than the sample period 10^{th} percentile (MKT < P10). Specification (2) presents performance of bear beta quintiles during normal times. Specifications (3) and (4) reports the results when excess market returns are negative and positive respectively. The sample period is from January 1998 to December 2017. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
(1) MKT < P10						
Equal-weighted return (%)	-1.44	-1.62	-1.90	-2.45	-4.28	-2.85
	(-2.47)	(-4.85)	(-8.66)	(-12.19)	(-8.77)	(-2.82)
(2) MKT > P10						
Equal-weighted return (%)	1.13	0.80	0.73	0.76	0.80	-0.33
	(7.06)	(8.42)	(7.48)	(6.61)	(7.13)	(-2.61)
(3) MKT < 0						
Equal-weighted return (%)	-0.62	-0.59	-0.65	-0.90	-1.78	-1.16
	(-2.26)	(-2.52)	(-2.92)	(-4.26)	(-5.62)	(-3.06)
(4) MKT > 0						
Equal-weighted return (%)	1.78	1.26	1.15	1.25	1.55	-0.23
	(7.09)	(10.24)	(8.09)	(6.41)	(6.67)	(-1.13)

Table 6: Fama and MacBeth regressions

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund excess returns in month $t + 1$ on bear beta (β^{BEAR}) and other control variables measured at the end of month t over the sample period from January 1998 to December 2017. Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. The control variables include different fund characteristics, manager skill measure, and other measures of risks. A detailed definition of these variables is provided in Appendix A. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

MODEL	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	0.53	0.20	0.18	0.19	0.20	0.10	0.12
	(4.42)	(1.64)	(1.68)	(1.61)	(1.78)	(0.72)	(1.12)
β^{BEAR}	-0.59	-0.35	-0.25	-0.29	-0.33	-0.22	-0.29
	(-3.63)	(-3.72)	(-3.24)	(-3.30)	(-3.33)	(-3.79)	(-3.05)
Size		-0.02	-0.01	-0.02	-0.01	-0.01	0.00
		(-1.23)	(-1.01)	(-1.21)	(-1.08)	(-0.86)	(-0.39)
Age		0.00	0.00	0.00	0.00	0.00	0.00
		(-0.20)	(-0.18)	(-0.33)	(0.38)	(-0.42)	(0.06)
Min Investment		0.01	0.01	0.01	0.01	0.01	0.01
		(2.82)	(2.69)	(2.88)	(2.89)	(2.46)	(2.14)
Management Fee		-0.02	-0.01	-0.02	-0.01	-0.02	-0.01
		(-0.70)	(-0.39)	(-0.91)	(-0.42)	(-0.88)	(-0.30)
Incentive Fee		0.00	0.00	0.00	0.00	0.00	0.00
		(1.41)	(1.35)	(1.65)	(1.70)	(1.26)	(1.38)
Lock Up		0.00	0.00	0.00	0.00	0.00	0.00
		(0.75)	(0.32)	(0.95)	(0.39)	(0.66)	(0.07)
Redemption		0.01	0.01	0.02	0.02	0.01	0.01
		(0.54)	(0.42)	(0.76)	(0.64)	(0.29)	(0.62)
Leverage		-0.03	-0.02	-0.04	-0.04	-0.02	-0.03
		(-1.46)	(-1.16)	(-1.67)	(-1.72)	(-1.34)	(-1.60)
Hurdle		-0.06	-0.06	-0.06	-0.06	-0.06	-0.05
		(-1.43)	(-1.63)	(-1.46)	(-1.47)	(-1.38)	(-1.40)
HWM		0.00	0.01	0.00	-0.01	0.01	0.00
		(-0.14)	(0.24)	(-0.21)	(-0.66)	(0.33)	(-0.10)
Offshore		-0.02	-0.01	-0.02	-0.03	-0.01	-0.02
		(-0.76)	(-0.39)	(-0.80)	(-1.09)	(-0.42)	(-0.66)
Past return (12M)		1.62	1.73	1.63	1.59	1.84	1.80
		(5.68)	(7.33)	(5.30)	(6.67)	(7.36)	(6.20)
Ret VOL (24M)		4.04	3.11	4.37	3.96	3.15	3.71
		(1.65)	(1.87)	(1.93)	(2.06)	(1.94)	(2.69)
Ret SKEW (24M)		0.03	0.05	0.02	0.04	0.05	0.04
		(0.92)	(2.03)	(0.68)	(1.22)	(2.20)	(1.89)
Ret KURT (24M)		0.00	0.00	-0.01	0.00	0.00	0.00
		(-0.39)	(-0.45)	(-0.55)	(-0.28)	(-0.24)	(0.27)

β^{MKT}			0.21				0.33
			(0.98)				(1.54)
$\beta^{\Delta VOL}$				-0.01			0.07
				(-0.05)			(0.43)
$\beta^{\Delta SKEW}$				-0.91			-0.78
				(-1.57)			(-1.75)
TailRisk					0.11		-0.20
					(0.69)		(-3.14)
β^{UNC}						0.03	0.01
						(1.64)	(0.75)
β^{RIX}						-0.01	-0.07
						(-0.14)	(-0.75)
R2						-0.08	-0.07
						(-0.68)	(-0.70)
SDI						-0.06	0.02
						(-0.86)	(0.47)
Downside Return						-0.02	-0.01
						(-0.60)	(-0.35)
Adjusted R^2	0.03	0.16	0.22	0.19	0.19	0.23	0.28

Table 7: Association between bear beta and returns in different market states

The table shows results from Fama and Macbeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on bear beta (β^{BEAR}) and a series of control variables in different subperiods. The control variables included are the same with specification (7) of Table 6. Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. We present only the coefficients on bear beta (β^{BEAR}) and market beta (β^{MKT}); the coefficients for the rest of the variables are suppressed for the sake of brevity. MKT denotes the excess return of the market. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

MODEL	(1) MKT < P10	(2) MKT > P10	(3) MKT < 0	(4) MKT > 0
β^{BEAR}	-1.15	-0.20	-0.67	-0.06
	(-2.75)	(-1.83)	(-2.62)	(-0.42)
β^{MKT}	-6.83	1.13	-2.61	2.13
	(-10.96)	(5.35)	(-7.40)	(6.21)
Control variables	Yes	Yes	Yes	Yes
Average adjusted R^2	0.43	0.27	0.30	0.28
Number of months	24	216	91	149

Table 8: Bear beta effect during periods of increasing versus decreasing bear concern

The table shows results from Fama and Macbeth (1973) cross-sectional regressions of one-month ahead hedge fund excess returns on bear beta (β^{BEAR}) and a series of control variables during increasing versus decreasing bear concern states. We define increasing (decreasing) bear concern states as periods of positive (negative) market hedged Bear factor. Market hedged Bear factor is the component of the Bear factor that is orthogonal to the market excess returns. In month t, it is equal to the intercept coefficient plus the month t residual from a regression of the Bear factor on the market excess returns over the past 24 months. The control variables included are the same with specification (7) of Table 6. We present only the coefficients on bear beta (β^{BEAR}) and market beta (β^{MKT}); the coefficients on other control variables are suppressed for the sake of brevity. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

MODEL	(1) Market hedged Bear factor < 0	(2) Market hedged Bear factor > 0
β^{BEAR}	-0.49	0.44
	(-3.50)	(3.16)
β^{MKT}	0.04	1.41
	(0.15)	(4.41)
Control variables	Yes	Yes
Average adjusted R^2	0.26	0.38
Number of months	189	51

Table 9: Determinants of bear betas

The table presents the average intercepts, average coefficients, and average adjusted R^2s from Fama and MacBeth (1973) cross-sectional regressions of hedge fund bear beta (β^{BEAR}) on contemporaneous fund characteristics and risk attributes over the period from December 1997 to November 2017. Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. A detailed definition of different fund characteristics and other measures of risks is provided in Appendix A. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

MODEL	(1)	(2)	(3)
Intercept	0.00	-0.03	0.00
	(0.01)	(-0.63)	(-0.15)
Size	0.00		0.00
	(1.18)		(0.83)
Age	0.00		0.00
	(1.82)		(1.90)
Ret VOL (24M)	0.07		-0.16
	(0.18)		(-0.29)
Ret SKEW (24M)	0.10		0.09
	(6.00)		(5.89)
Ret KURT (24M)	0.00		0.00
	(-1.51)		(-1.56)
Fund return (12M)	-0.29		-0.27
	(-2.15)		(-2.30)
Min Investment		0.00	0.00
		(1.19)	(1.47)
Management Fee		-0.02	-0.02
		(-1.97)	(-2.24)
Incentive Fee		0.00	0.00
		(1.85)	(1.05)
Lock Up		0.00	0.00
		(0.38)	(0.84)
Redemption		-0.01	0.00
		(-1.48)	(-0.32)
Leverage		0.01	0.01
		(2.15)	(1.68)
Hurdle		-0.04	-0.02
		(-2.73)	(-1.98)
HWM		0.01	0.01
		(1.08)	(1.17)
Offshore		-0.04	-0.03
		(-2.73)	(-3.05)
Adjusted R^2	0.14	0.03	0.16

Table 10: Bear beta versus skills at exploiting rare disaster concern

The table investigates the difference between bear beta and skills at exploiting rare disaster concern. For consistency with Gao, Gao, and Song (2018), all findings are based on the period from January 1998 to December 2011. Panel A reports the performance of decile portfolios of hedge funds sorted by the betas (or sensitivities) with respect to various versions of the RIX index unconditional over the full sample period or conditional on market crashes (MKT < P10) versus normal times. These betas are estimated by regressing hedge fund excess returns on different versions of the RIX index controlling for the market excess returns over a 24-month rolling window. At the end of each month from December 1997 to November 2011, we sort hedge funds into deciles according to their betas on different versions of the RIX index. We rebalance the portfolios each month; thus, the portfolio returns are from January 1998 to December 2017. We measure the average equal-weighted returns for several decile portfolio and for D10-D1 portfolio. We present four sets of results. Specification (1) uses the RIX index that is made publicly available by George Gao. Specification (2) uses our replicated RIX index. Specification (3) uses a RIX index which is constructed from S&P500 put options. Specifications (4) use RETRIX, which is the average daily return within a month of a portfolio of S&P500 index put options that form RIX. Panel B reports the performance of hedge fund portfolios that are sorted on RIX betas and RETRIX betas. In Panel B.1, we first sort funds based on RETRIX betas into quintiles and within each quintile, we further sort funds into five portfolios based on RIX betas. In Panel B.2, we first sort funds based on RIX betas into quintiles and within each quintile, we sort funds into five portfolios based on RETRIX betas. We rebalance these portfolios each month and report equal-weighted as well as risk-adjusted returns. All returns and alphas are in monthly percentages. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

Panel A: Univariate portfolio-level analysis, sorted on betas with respect to various versions of the RIX index

	Full sample: Jan 1998 - Dec 2010					MKT < P10			MKT > P10		
	D1	D5	D10	D10-D1	FH alpha	D1	D10	D10-D1	D1	D10	D10-D1
(1) Sort by fund's sensitivity to RIX index obtained from Gao et al. (2018)											
Returns (%)	0.34	0.43	1.11	0.77	0.80	-5.43	-1.48	3.94	1.00	1.41	0.42
	(0.91)	(2.47)	(4.57)	(2.51)	(3.11)	(-4.10)	(-2.28)	(2.42)	(3.90)	(5.78)	(1.96)
(2) Sort by fund's sensitivity to our replicated RIX index											
Returns (%)	0.32	0.44	1.04	0.72	0.83	-5.79	-1.32	4.47	1.04	1.36	0.32
	(0.77)	(2.65)	(4.80)	(2.17)	(3.09)	(-4.50)	(-2.25)	(3.06)	(3.90)	(5.78)	(1.43)
(3) Sort by fund's sensitivity to our replicated RIX index that uses only options from S&P500											
Returns (%)	0.44	0.48	0.95	0.52	0.64	-5.10	-1.62	3.48	1.11	1.28	0.17
	(1.05)	(2.88)	(4.50)	(1.47)	(2.16)	(-3.45)	(-1.91)	(1.67)	(3.97)	(5.91)	(0.79)
(4) Sort by fund's sensitivity to RETRIX											
Returns (%)	1.10	0.47	0.35	-0.75	-0.83	-2.41	-4.09	-1.69	1.51	0.87	-0.64
	(4.07)	(2.91)	(1.15)	(-2.98)	(-2.87)	(-9.35)	(-7.97)	(-2.33)	(6.04)	(4.01)	(-3.71)

Panel B: Bivariate dependent portfolio-level analysis, sorted on RIX betas and RETRIX betas

Panel B.1: First sort on RETRIX betas, then on RIX beta

	Low RIX beta	2	3	4	High RIX beta	Q5-Q1	FH-alpha
Low RETRIX beta	0.71	0.72	0.65	0.88	1.37	0.66 (2.19)	0.63 (2.14)
2	0.46	0.51	0.51	0.54	0.77	0.31 (1.73)	0.32 (2.01)
3	0.51	0.47	0.39	0.50	0.71	0.20 (1.46)	0.21 (1.58)
4	0.40	0.42	0.39	0.49	0.75	0.35 (2.06)	0.41 (2.86)
High RETRIX beta	0.23	0.36	0.27	0.55	0.75	0.52 (1.84)	0.62 (2.40)
Average	0.46	0.50	0.44	0.59	0.87	0.41 (2.13)	0.44 (2.65)

Panel B.2: First sort on RIX betas, then on RETRIX betas

	Low RETRIX beta	2	3	4	High RETRIX beta	Q5-Q1	FH-alpha
Low RIX beta	0.76	0.48	0.35	0.30	0.13	-0.63 (-2.00)	-0.83 (-2.10)
2	0.65	0.53	0.46	0.41	0.40	-0.26 (-1.70)	-0.39 (-2.54)
3	0.60	0.45	0.43	0.40	0.35	-0.25 (-2.45)	-0.33 (-2.83)
4	0.75	0.62	0.50	0.54	0.44	-0.31 (-2.50)	-0.36 (-2.80)
High RIX beta	1.31	0.96	0.76	0.76	0.79	-0.52 (-2.73)	-0.62 (-3.30)
Average	0.81	0.61	0.50	0.48	0.42	-0.39 (-2.65)	-0.51 (-2.99)

Table 11: Performance of bear beta-sorted hedge fund portfolios in different investment style categories

The table reports the performance of bear beta-sorted hedge fund portfolios for each investment style. Bear beta is estimated from a regression of hedge fund excess returns on the Bear factor controlling for the market excess returns over the past 24 months with a requirement of at least 18 months of non-missing fund returns. At the end of each month from December 1997 to November 2017, hedge funds of a specific investment style are sorted into five portfolios on the basis of their bear betas. Quintile 1 (5) consists of funds with the lowest (highest) bear betas. We rebalance the portfolios each month; thus, the portfolio returns are from January 1998 to December 2017. For each style, we present the average bear beta, the average equal-weighted returns and Fung-Hsieh alphas (in percentage terms) for each quintile as well as for the Q5-Q1 portfolio. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
			Event-Driven			
Average Bear Beta	-0.43	-0.14	-0.04	0.07	0.41	0.84
Equal-weighted returns	0.82	0.55	0.55	0.48	0.47	-0.35
	(4.51)	(4.21)	(4.77)	(3.15)	(2.25)	(-2.83)
FH alpha	0.58	0.37	0.40	0.30	0.17	-0.41
	(4.95)	(4.21)	(5.17)	(2.67)	(1.78)	(-3.54)
			Relative Value			
Average Bear Beta	-0.47	-0.13	-0.03	0.06	0.34	0.80
Equal-weighted returns	0.92	0.63	0.50	0.35	0.20	-0.72
	(5.30)	(6.29)	(5.31)	(2.72)	(0.96)	(-3.05)
FH alpha	0.78	0.55	0.41	0.24	0.02	-0.76
	(4.85)	(6.93)	(5.98)	(2.39)	(0.11)	(-2.96)
			Long-Short Equity			
Average Bear Beta	-0.76	-0.23	-0.02	0.18	0.69	1.44
Equal-weighted returns	0.86	0.64	0.59	0.56	0.61	-0.25
	(3.37)	(3.57)	(3.59)	(2.95)	(2.47)	(-1.80)
FH alpha	0.46	0.29	0.25	0.14	0.12	-0.35
	(2.27)	(2.19)	(2.43)	(1.46)	(0.87)	(-2.17)
			Global Macro			
Average Bear Beta	-0.62	-0.19	0.00	0.18	0.65	1.27
Equal-weighted returns	0.92	0.76	0.49	0.41	0.22	-0.70
	(4.93)	(4.96)	(3.59)	(3.19)	(0.80)	(-3.31)
FH alpha	0.79	0.61	0.35	0.28	0.02	-0.77
	(4.14)	(4.11)	(2.37)	(2.33)	(0.09)	(-4.18)
			CTA			
Average Bear Beta	-0.56	-0.15	0.02	0.20	0.76	1.32
Equal-weighted returns	0.70	0.38	0.25	0.24	0.18	-0.52
	(4.19)	(2.55)	(2.26)	(3.11)	(1.09)	(-2.98)
FH alpha	0.68	0.35	0.26	0.25	0.15	-0.53
	(4.27)	(2.18)	(2.43)	(2.99)	(0.80)	(-2.81)

			Equity Market Neutral			
Average Bear Beta	-0.34	-0.12	-0.02	0.08	0.36	0.70
Equal-weighted returns	0.42	0.32	0.29	0.23	0.22	-0.21
	(6.74)	(6.98)	(6.49)	(3.21)	(2.65)	-2.47
FH alpha	0.36	0.26	0.26	0.17	0.15	-0.21
	(4.74)	(5.75)	(5.14)	(2.49)	(1.99)	-2.06
			Multi-Strategy			
Average Bear Beta	-0.60	-0.18	0.01	0.19	0.70	1.29
Equal-weighted returns	0.92	0.67	0.48	0.39	0.31	-0.61
	(5.26)	(5.26)	(5.95)	(4.64)	(2.50)	(-2.99)
FH alpha	0.97	0.68	0.45	0.34	0.26	-0.71
	(4.35)	(4.01)	(4.46)	(3.76)	(2.13)	(-2.94)
			Sector			
Average Bear Beta	-0.53	-0.12	0.10	0.34	0.94	1.47
Equal-weighted returns	1.10	0.62	0.76	0.59	0.51	-0.58
	(2.67)	(2.41)	(2.07)	(1.82)	(1.43)	(-2.01)
FH alpha	0.64	0.28	0.38	0.16	0.00	-0.64
	(1.96)	(1.25)	(1.26)	(0.64)	(-0.01)	(-1.94)
			Fund of Funds			
Average Bear Beta	-0.31	-0.12	-0.05	0.03	0.22	0.53
Equal-weighted returns	0.53	0.46	0.41	0.39	0.25	-0.28
	(3.96)	(3.57)	(3.22)	(2.75)	(1.71)	(-3.68)
FH alpha	0.39	0.31	0.26	0.24	0.07	-0.32
	(3.09)	(2.81)	(2.49)	(2.04)	(0.67)	(-3.28)

Table 12: Long-term predictive power of bear beta

The table reports the long-term performance of bear beta-sorted hedge fund quintle portfolios. All portfolios are equal-weighted. In Panel A, we report the time-series average of kth-month ahead excess returns for each of the hedge fund quintiles formed each month on the basis of bear beta as well as the average kth-month ahead return and Fung-Hsieh alpha differences between the high and low bear beta quintiles (Q5-Q1). Panel B presents results for the bear beta-sorted quintile portfolios with holding periods ranging from 3 months to 24 months. We implement the independently managed portfolio strategy of Jegadeesh and Titman (1993) to deal with the overlapping nature of the long-horizon returns and compute average monthly excess returns. We report the monthly average returns for each quintile as well as the average return and Fung-Hsieh alpha differences for the Q5-Q1 portfolio. In Panel C, we perform the same analysis as in Panel B except that we leave a one-month gap between the portfolio formation month and the month in which portfolio returns start being calculated. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

Panel A: Predictive power of bear beta for kth month ahead returns

$t+k$ month ahead returns	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$
Q1 (Low β^{BEAR})	0.89	0.84	0.77	0.77	0.77	0.74	0.71	0.69
Q2	0.57	0.56	0.54	0.53	0.52	0.50	0.49	0.54
Q3	0.48	0.47	0.47	0.44	0.46	0.46	0.46	0.48
Q4	0.41	0.41	0.41	0.42	0.42	0.45	0.45	0.49
Q5 (High β^{BEAR})	0.29	0.32	0.35	0.39	0.42	0.45	0.52	0.56
Q5-Q1	-0.60	-0.53	-0.42	-0.38	-0.34	-0.29	-0.19	-0.13
	(-3.57)	(-3.45)	(-3.61)	(-3.72)	(-4.02)	(-3.19)	(-1.91)	(-1.03)
FH Alpha	-0.75	-0.65	-0.49	-0.46	-0.41	-0.37	-0.28	-0.20
	(-3.69)	(-3.61)	(-4.05)	(-3.73)	(-4.44)	(-2.97)	(-2.56)	(-1.67)

Panel B: Predictive power of bear beta for long-term holding period returns

Holding for the next	3 months	6 months	9 months	12 months	15 months	18 months	21 months	24 months
Q1 (Low β^{BEAR})	0.87	0.83	0.80	0.76	0.74	0.70	0.67	0.64
Q2	0.56	0.55	0.56	0.55	0.54	0.52	0.52	0.50
Q3	0.47	0.46	0.49	0.48	0.48	0.46	0.45	0.44
Q4	0.41	0.41	0.47	0.47	0.46	0.44	0.43	0.42
Q5 (High β^{BEAR})	0.29	0.35	0.46	0.46	0.48	0.46	0.46	0.46
Q5-Q1	-0.58	-0.49	-0.34	-0.30	-0.27	-0.23	-0.21	-0.18
	(-3.53)	(-3.79)	(-2.99)	(-3.18)	(-3.28)	(-2.97)	(-2.63)	(-2.30)
FH Alpha	-0.71	-0.58	-0.39	-0.34	-0.29	-0.25	-0.23	-0.19
	(-3.66)	(-3.89)	(-3.15)	(-3.05)	(-2.65)	(-2.35)	(-2.14)	(-1.88)

Panel C: Long-term holding period with a 1-month lag between ranking and performance months

1-month lag and holding for the next	3 months	6 months	9 months	12 months	15 months	18 months	21 months	24 months
Q1 (Low β^{BEAR})	0.84	0.79	0.75	0.72	0.70	0.68	0.66	0.64
Q2	0.57	0.55	0.54	0.54	0.53	0.53	0.53	0.52
Q3	0.48	0.47	0.47	0.47	0.47	0.47	0.47	0.48
Q4	0.42	0.43	0.44	0.44	0.44	0.45	0.45	0.46
Q5 (High β^{BEAR})	0.34	0.39	0.43	0.46	0.48	0.50	0.51	0.53
Q5-Q1	-0.50	-0.40	-0.32	-0.26	-0.22	-0.18	-0.15	-0.11
	(-3.55)	(-3.66)	(-3.35)	(-2.97)	(-2.64)	(-2.20)	(-1.75)	(-1.28)
FH Alpha	-0.62	-0.51	-0.42	-0.36	-0.31	-0.28	-0.25	-0.21
	(-3.82)	(-3.98)	(-3.87)	(-3.47)	(-3.08)	(-2.77)	(-2.41)	(-2.02)

Table 13: Robustness checks

The table reports the results from a series of robustness checks with respect to the average returns and Fung-Hsieh alphas of hedge fund portfolios sorted by bear beta. At the end of each month from December 1997 to November 2017, we sort hedge funds into quintiles according to their bear beta level. Quintile 1 (5) consists of funds with the lowest (highest) bear betas. We hold these quintile portfolios for one month and present the average returns and alphas for each quintile and for the Q5-Q1 portfolio. In specification (1), average returns are weighted by the fund's AUM at the time of portfolio formation. In specifications (2) and (3), bear beta is estimated over the 12-month and 36-month rolling window, respectively. In specifications (4) and (5), we construct the Bear portfolio by defining the bear region as states in which the market excess return is two and one standard deviations below zero, respectively. In specification (6), we drop the short put position from the Bear portfolio and use only the long put position. In specification (7), we set -100% on returns of drop-out funds. All returns and alphas are in monthly percentages. Newey and West (1987) t-statistics with lag length equal to 24 are reported in parentheses.

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
(1) Value-weighted returns						
Value-weighted returns	0.83	0.52	0.44	0.40	0.20	-0.63
	(6.01)	(4.74)	(4.38)	(3.31)	(1.30)	(-3.42)
FH alpha	0.67	0.38	0.30	0.22	-0.06	-0.73
	(4.38)	(4.20)	(4.03)	(2.50)	(-0.51)	(-3.40)
(2) Horizon of 12 months						
Equal-weighted returns	0.88	0.57	0.51	0.47	0.39	-0.50
	(5.52)	(4.91)	(4.26)	(3.42)	(1.69)	(-2.75)
FH alpha	0.69	0.41	0.33	0.24	0.01	-0.67
	(4.56)	(4.69)	(4.18)	(2.82)	(0.10)	(-3.36)
(3) Horizon of 36 months						
Equal-weighted returns	0.82	0.56	0.48	0.44	0.39	-0.42
	(5.96)	(5.20)	(4.30)	(3.66)	(2.67)	(-4.30)
FH alpha	0.58	0.39	0.32	0.26	0.12	-0.46
	(3.51)	(3.32)	(2.93)	(2.61)	(1.24)	(-3.38)
(4) Beta Bear 2σ						
Equal-weighted returns	0.81	0.52	0.46	0.46	0.38	-0.43
	(4.83)	(4.74)	(4.00)	(3.63)	(2.26)	(-3.16)
FH alpha	0.61	0.35	0.30	0.26	0.09	-0.52
	(3.57)	(3.89)	(3.28)	(2.94)	(0.96)	(-3.18)
(5) Beta Bear 1σ						
Equal-weighted returns	0.84	0.57	0.47	0.42	0.33	-0.51
	(5.50)	(4.97)	(4.00)	(3.20)	(1.85)	(-3.65)
FH alpha	0.69	0.42	0.31	0.21	0.00	-0.69
	(4.10)	(3.88)	(3.33)	(2.31)	(-0.05)	(-4.09)
(6) Beta OTMPUT						
Equal-weighted returns	0.80	0.56	0.48	0.43	0.35	-0.45
	(4.71)	(4.61)	(4.07)	(3.42)	(2.36)	(-3.54)
FH alpha	0.60	0.40	0.32	0.22	0.07	-0.53
	(3.71)	(3.69)	(3.39)	(2.61)	(0.80)	(-3.30)

(7) Delisting returns						
Equal-weighted returns	-0.18	-0.35	-0.46	-0.59	-0.99	-0.80
	(-0.92)	(-1.97)	(-2.34)	(-3.20)	(-3.91)	(-4.41)
FH alpha	-0.37	-0.52	-0.63	-0.79	-1.30	-0.93
	(-1.95)	(-2.98)	(-3.43)	(-4.87)	(-7.41)	(-4.46)