Option-Implied Tail Risk, Timing by Hedge Funds, and Performance*

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April 21, 2017

ABSTRACT

This paper newly focuses on an unexplored dimension of fund managers' timing ability; market-wide tail risk implied by information in option market. We investigate whether hedge fund managers can strategically time market tail risk implied by option through adjusting their portfolios' market exposure to changes of market tail risk. Using an extensive sample of 6147 equity-oriented hedge funds from 1996 to 2012, we find strong evidence of tail risk timing ability of hedge fund managers. We conduct bootstrap analysis and confirm that our tail risk timing ability is not attributed to pure luck. Furthermore, tail risk timing ability brings a significant economic value to investors. Specifically, in out-of-sample tests, top-ranked hedge funds outperform bottom-ranked funds by 5-7% annually after adjusting common risk factors. Also, we find that managers' tail risk timing skill persists over time, suggesting that hedge fund managers' tail risk timing ability reflects true managerial skill. Our overall results are robust to various hedge fund characteristics, subsample or sub-period analysis, the use of alternative timing abilities, and other hedge funds' managerial skills. All the empirical examination emphasizes the role of market-wide option-implied tail risk in hedge fund managers' skill and their performance.

Keywords: Option-implied tail risk, Hedge funds, Tail risk timing, Fund performance

JEL classification: G11, G2

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1. Introduction

Hedge funds often make headlines because of spectacular losses due to infrequent but dramatic and unexpected events.[1] As Stulz (2007) argues, hedge fund managers are normally considered as pursuing strategies that generate steadily positive returns or alphas but sometimes bring a tremendous loss as to fail the hedge fund company itself. Most of those failures of hedge funds are related to 'tail' events in capital markets. For example, Tiger Management closed and Quantum Fund recorded substantial losses in 2000 due to stock market crash after IT-tech bubble burst. In this way, the 'tail' event of capital market has played a very crucial role in the life cycle of hedge fund industry.

Then, can hedge funds managers, who have been considered as a sophisticated and professional investors, forecast and react strategically changes in market 'tail' risk? After the pioneering work of Treynor and Mazuy (1966), a large number of literature has attempted to identify the presence of fund managers' timing ability and academics has shown a lot of interest on timing ability of professional managers.[2] Nevertheless, the majority of studies have focused on the ability to time market returns and there is paucity of studies identifying the timing ability for other dimensions of market conditions. Under this circumstance, the main objective of this study is to investigate professional fund managers' timing ability, especially in hedge fund industry, with respect to a critical but unexplored dimension of market conditions – market tail risk. Specifically, we try to investigate the following research questions. First, can hedge fund managers strategically time market tail risk by adjusting fund betas in anticipation of future market tail events? Second, if they can, how much economic value does this tail risk timing skill add to fund investors? Addressing those questions is essential to improving our comprehension of managerial skills of hedge funds and the economic consequences of these skills. Also, these issues are important to an understanding of the role of tail risk in the hedge fund industry.

We examine hedge funds' tail risk timing ability for several reasons. First, as aforementioned, market-wide tail risk plays a key role to hedge funds managers, in that infrequent but dramatic market events, especially downside events (or left-tail events) can incur undesirable huge losses over a short period of time to hedge funds, resulting in direct tremendous damage to portfolios and then investors' welfare. Particularly, Kelly and Jiang (2012) argues that an increase in market-wide tail risk is

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[1] For instance, the Long-Term Capital Management (LTCM) collapsed in 1998 because Russia defaulted on its debt in August 1998; Tiger Management closed after IT tech stock crash and Quantum Fund lost 11 percent of its capital in five days when the tech-stock bubble burst. By May 2000, losses were 22 percent; Marin Capital closed in June 2005 after sharp losses triggered by the downgrading of General Motors to junk bond status; In September 2006, a large hedge fund, Amaranth, reported losses of more than $6 billion apparently incurred in only one month, representing a negative return over that month of roughly 66 percent because the hedge fund's energy trading strategy failed due to ill-timed speculation in natural gas prices. Due to mild winter conditions and a meek hurricane season, natural gas prices were weak at that time; The liquidation of two Bear Stearns hedge funds in August 2007 due to subprime mortgage financial crisis.

[2] See, Fama, 1972; Jensen, 1972; Merton, 1981; Henriksson and Merton, 1981; Chang and Lewellen, 1984; Henriksson, 1984; Admati, Bhattacharya, Pfleiderer, and Ross, 1986; Jagannathan and Kprajczyk, 1986; Grinblatt and Titman, 1989; Ferson and Schadt, 1996; Becker, Ferson, Myers, and Schill, 1999; Busse, 1999; Goetzmann, Ingersoll, and Ivkovich, 2000; Bollen and Busse, 2001; Jiang, 2003; Chen, 2007; Chen and Liang, 2007; Jiang, Yao, and Yu, 2007; Chen, Ferson, and Peters, 2010; Cao, Chen, Liang, and Lo, 2013; Bodnaruk, Chokaev, Simomov, 2015; and Chen, Han, and Pan, 2016. With a few exceptions, most empirical results indicate little evidence of timing ability in mutual funds or pension funds.

associated with a decline of the value of aggregate hedge fund portfolios. Moreover, the collapses of large hedge funds such as Long-Term Capital Management (LTCM) in 1998 and Bear Stearns in 2007 were accompanied by huge market crashes and those events exert significant adverse effects on the stability of the entire financial system. In this regard, the investigation about whether hedge fund managers actually possess timing ability to market tail risk has a great importance in economic perspectives. Second, hedge funds have enjoyed explosive growth over the last two decades and they have long been regarded as the most sophisticated and professional investors. Thus, if professional asset managers strategically time market, we would naturally ask for whether these professional managers have the timing ability for market tail risk. Also, extensive literatures have suggested evidence for a positive risk-adjusted performance of hedge funds. (e.g., Brown, Goetzmann, and Ibbotson, 1999; Fung, Hsieh, Naik and Ramadorai, 2008; and Jagannathan, Malakhov, and Novikov, 2010) Hence, it seems natural to investigate whether tail risk timing ability of hedge fund managers contributes to the superior performance of hedge funds. Finally, the previous studies have documented that hedge funds use dynamic trading strategies and have time-varying systematic risk exposures (Fung and Hsieh, 1997, 2001; Agarwal and Nail, 2004; Cao, Chen, Liang, and Lo, 2013; Patton and Ramadorai, 2013). Considering their distinct feature of time-varying market exposure and the great impact of market downside risk on them, it is reasonable to investigate the presence of timing ability in hedge fund industry.

To investigate timing ability of hedge fund managers, we utilize well-established timing framework proposed by Treynor and Mazuy (1966) and apply market-wide tail risk measure implied by information in option market. The past studies document that information in option prices not only propose a contemporaneous state of underlying asset but also provide valuable forecasts of features of the future payoff distributions in the underlying asset (e.g., Bates, 1991; Jackwerth and Rubinstein, 1996). In general, precipitous and rapid decline in market capitalization is usually accompanied by a rare events, is sometimes exacerbated by fear, and persists for a few months. In this regards, we judge that the information of market crash risk and current market state should be contained in option market. Furthermore, the past literature shows that market-wide high-moment risks implied by index option has a significant effect on hedge fund returns (Agarwal et al, 2010). To construct our option-implied tail risk timing model, we first measure the option-implied market tail risk by using the information contained in risk-neutral moments (Bakshi, Kapadia, and Madan, 2003) and a slope of the implied volatility smirk of out-of-the-money (OTM) put options[3] (e.g., Bollen and Whaley, 2004), which are widely used in the previous studies and also highly correlated to market tail risk. Then, we make a single index of option-implied tail risk using a PCA analysis. Our timing model is similar to volatility timing

[3] As noted by Kelly and Jiang (2014), the realized cross-sectional tail risk measure proposed by them has significant correlation with the risk-neutral moments and the slope of OTM put volatility smirk.

model (e.g., Busse, 1999), because the past studies use VIX index as a proxy for market volatility, which is also implied by option. However, to the best of our knowledge, this study is the first paper applying option-implied tail risk measure to examine hedge fund managers' timing ability.

Using the extensive sample of 6147 equity-oriented hedge funds on the periods from 1996 to 2012, we empirically investigate tail risk timing ability at the individual level and check the economic value of this tail risk timing. At first, from the regression analysis for each fund, we find economically and statistically significant evidence of tail risk timing ability at the individual fund level, in contrast to aggregate fund level, in that the time-series of aggregate fund returns do not show significant timing ability for option-implied market tail risk. Furthermore, to distinguish this statistical significance of individual funds' timing ability from pure luck, we conduct a bootstrap analysis followed by the previous literature (e.g., Cao, Chen, Liang, and Lo, 2013). The result suggests that our empirical findings are not attributed to pure luck or multi-sample bias, and there exists professional hedge fund managers exhibiting significant tail risk timing ability.

Secondly, we conduct simple univariate portfolio analysis for several holding periods to check top-ranked hedge funds generate significant future abnormal returns to examine whether the tail risk timing ability adds economic value to fund investors. We evaluate out-of-sample monthly excess returns and risk-adjusted returns for decile equal-weighted portfolios of funds based on the past timing tail risk skills with twelve-month holding periods, and the results indicate that hedge funds in the greatest tail risk timing portfolio (top timers) outperform others in the lowest tail risk timing portfolio (bottom timers) by 0.50% per month (6.11% per year) and 0.55% per month (6.84% per year) in terms of excess returns and alphas, respectively. In addition, we conduct Fama-MacBeth (1973) cross-sectional regression to confirm our economic value from tail risk timing skill is robust to other fund characteristics which are associated to future fund performance. The results indicate that our inference on tail risk timing ability remains after other fund characteristics are controlled for. Third, we examine whether tail risk timing ability persists over time in out-of-sample tests based on portfolio analysis. Our simple analysis find strong evidence of persistence in the tail risk timing ability of hedge funds, in that, the future tail risk timing coefficient estimated from our option-implied tail risk timing model has monotonic relation with the past timing coefficient, implying that the tail risk timing ability reflects true managerial skill and those professional hedge fund managers exploit significant alphas from the capital market.

We further conduct a variety of sensitivity analyses to confirm the robustness of our findings. First, we test whether a specified group of hedge funds sample causes biases to our main inferences about tail risk timing ability. In details, there is possibility that our results on tail risk timing might be driven by usage of leverage and redemption constraints or by the impact of large funds' trading on overall market conditions, such as market tail risk. Second, we are concerned that our results could be driven by specific short periods such as 2008-2009 financial crisis periods when extreme market tail events occurred. Thus, to mitigate the biases caused by infrequent nature of extreme events, we repeat our main analysis using the sub-sample of pre-crisis periods (January 1996 to December 2007). In summary, we rerun our main estimation approach based on the above concerns and find our tail risk timing skill is still robust and our main inference on tail risk timing ability does not change.

In addition, one might be concerned that various dimensions of market conditions, such as market returns, volatility, liquidity, and even tail risk seem to be highly correlated with each other. Also, it is well-organized that hedge fund managers have significant timing skill with respect to these various kinds of market conditions.[4] In this regard, to alleviate concerns that our findings could be simply attributed to other types of timing skill, we explicitly control for other dimensions of timing ability in our base-line timing model, including market volatility and liquidity timing skill additionally. Our main results do not qualitatively and quantitatively change even after controlling for other timing aspects in our baseline timing model. Also, economic value driven by tail risk timing ability still remains robust to volatility and liquidity timing abilities, implying that managers' tail risk timing ability does matter for superior performance of funds.

Lastly, to check the possibility that our timing skill measure is not essentially different from other types of managerial skill measures, which appear to evaluate a similar aspect of managerial skills. Thus, we consider two kinds of other managerial skill proxies, which are likely to be highly related to our tail risk timing ability, including hedging skills proposed by Titman and Tiu (2011) and downside returns discussed in Sun, Whang, and Zheng (2014), then we conduct a cross-sectional regression to check the final robustness suggesting that tail risk timing ability still remain significant for future performance of hedge funds.

We contribute to the existing body of literature in several aspects. First, our paper largely extends the timing literature by suggesting a new dimension of hedge fund timing ability, i.e., timing for market-wide tail risk implied by option. Undoubtedly, the market-wide extreme event risk (or tail risk) has affected critically on the performance of professional fund managers, especially hedge fund managers. To the best of our knowledge, this paper is the first study to investigate the timing ability to market tail risk, and find that there exists hedge funds which can time the market by successfully adjusting their exposures to market as market-wide tail risk changes and those funds perform well in the future. Moreover, our paper provide comprehensive analysis regarding timing ability of hedge funds managers. Given the increasing importance of market tail risk concerns in entire asset management industry as noted by aforementioned anecdotes, we employ a large sample of equity-oriented hedge funds including funds of funds, instead of a limited group of hedge funds such as self-described market timing funds. Furthermore, we apply a bootstrap analysis to try to confirm that our main inferences are not attributed

[4] For instance, Bodnaruk, Chokaev, and Simonov (2015) argue that market return timing and downside risk timing could be identical if asset returns comove with market returns systematically regardless of direction. However, it has been shown that stocks commove more with the market when the market goes down rather than market goes up (Hong, Tu, and Zhou, 2007). Also, Bodnaruk et al. (2015) show that managers with higher forecasting ability are more likely to follow downside risk timing strategies beyond market return timing strategies.

to pure luck. Because hedge funds often have short histories and non-normally distributed returns, the bootstrap analysis enhances the reliability of our inferences. Finally, our results are robust to several potential sampling biases, timing ability for other market dimensions, and different managerial skill proxies, suggesting that our main arguments on tail risk timing of hedge funds and its economic value are economically significant.

The remainder of this paper is organized as follows. The next section describes the tail risk timing model and our option-implied tail risk measure. This is followed by the section that introduces the hedge fund sample we use in this study. The following two section provides the results of our main empirical findings and the several additional tests and robustness checks. The final section concludes this paper.

2. Option-Implied Tail Risk Timing Model

2 – 1 Tail Risk Timing Model

In this section, we build our tail-risk timing model to investigate market tail risk timing ability of hedge funds managers. Generally, market timing is simply regarded as a performance-enhancing strategy that adjusts funds' market exposure based on the manager's forecasts, resulting in a crucial source of superior performance. First, we start by utilizing well-established timing framework proposed by Treynor and Mazuy (1966).

In general, a timing model is based on the capital asset pricing model (CAPM) by assuming that a funds generate returns at time t+1 according to the following process

$$r_{p,t+1} = \alpha_p + \beta_{p,t} MKT_{t+1} + u_{p,t+1}, \qquad t = 0, \dots, T-1 \tag{1}$$

where $r_{p,t+1}$ is the excess monthly return (return in excess of the one-month Treasury bill rate) for fund *p* in month *t+1* and MKT_{t+1} is the excess return on the market portfolio. Eq. (1) allows the fund's market beta to vary over time. The time description in Eq. (1) follows the timing literature, in which the fund beta $\beta_{p,t}$ is determined by the manager in month *t* based on her forecast about market conditions in month *t+1*. Thus, managers strategically adjust their funds' market exposures based on their forecasts of future market conditions. In this setting, various timing models differ in the dimensions of the market conditions they concentrate on (e.g., volatility, liquidity, and sentiment).

Using a Taylor series expansion, existing timing models (e.g., Admati, Bhattacharya, Pfleiderer, and Ross 1986; and Ferson and Schadt, 1996) approximate the timer's market beta as a linear function of her forecast about market conditions by ignoring higher-order terms (e.g., Shanken, 1990). Following the priors, we can also obtain the generic form of such model specification:

$$\beta_{p,t} = \beta_p + \gamma_p E(market\ condition_{t+1} | I_t), \tag{2}$$

where I_t is the information set available to the fund manager in month *t*. In this specification, the coefficient γ_p indicates managers' timing skill, i.e., how market beta varies with forecasts about market conditions. In this paper, we try to explore an unexplored dimension of timing skill, namely, tail-risk timing - the ability to strategically adjust their portfolios' exposures on market to have a low loading on the market portfolio when the market tail risk is expected to be high. Therefore, we specify Eq. (3) as follows.

$$\beta_{p,t} = \beta_p + \gamma_p(Tail\ Risk_{m,t+1} + \upsilon_{t+1}), \quad (3)$$

where the expression in parentheses presents the manager's prediction (i.e., timing signal) about market tail risk and $Tail\ Risk_{m,t+1}$ is the measure of market tail risk in month *t+1*. Since it is unrealistic for a timer to have a perfect signal, υ_{t+1} denotes a forecast error unknown until *t+1*, which we assume to be independent with a zero mean. We measure market tail risk, i.e.,$Tail\ Risk_{m,t+1}$, using information extracted from option markets. Details on construction and description of tail risk are summarized in the next section.

Finally, we can specify the following tail-risk timing model specification by substituting Eq. (3) in Eq. (1) and incorporating the forecast error υ within the error term:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1} Tail\ Risk_{m,t+1} + \varepsilon_{p,t+1}. \quad (4)$$

The tail-risk timing model in Eq. (4) is in line with the existing models of market timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(MKT_{t+1} + \upsilon_{t+1})$], volatility timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(Vol_{m,t+1} - \overline{Vol_m} + \upsilon_{t+1})$], and liquidity timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(L_{m,t+1} - \overline{L_m} + \upsilon_{t+1})$] except that the market condition considered here is market tail risk. In our timing model, a negative timing coefficient γ_p implies that the fund strategically decreases the market exposure when the market tail risk is expected to be high.

In the estimation process, we additionally include several factors, which is most widely used in hedge fund literature. Specifically, we first consider the traditional three-factor of Fama and French (1993), i.e., market, size, book-to-market, and Carhart (1997) momentum factor. Furthermore, it is well known that hedge funds use dynamic strategies (e.g., Fund and Hsieh, 1997, 2001) and invest other asset classes like derivatives (e.g., Chen, 2011). Thus, we include a bond market factor, a credit spread factor, and three trend-following factors for currency, bonds and commodities proposed by Fung and Hsieh (2004). Finally, we also add the Pastor and Stambaugh (2003) liquidity factor to control for liquidity risk.

Throughout this paper, we estimate tail risk timing ability by focusing on the changes in market (MKT factor) exposure because the stock market exposure is the most closely related with our sample (equity-oriented hedge funds). Specifically, for each hedge fund with at least 24 monthly return observations, we perform the following tail-risk timing regression.

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1} Tail\ Risk_{m,t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1} \quad (5)$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1 and MKT_{t+1} is the excess return on the market portfolio in month t+1. $Tail\ Risk_{m,t+1}$ is the time-varying market tail risk in month t+1 described in Section 3.1. $f_{j,t+1}$ includes the various factors other than the equity market factor described in Section 3.2 (J = 8 in baseline case). The coefficient γ_p captures tail risk timing ability, and a significantly negative γ_p coefficient indicates that the funds tend to decrease its exposure to market when the market tail risk turns out to be high, implying successful tail risk timing.

2 – 2 Measure of Option-Implied Tail Risk

Market tail risk is basically defined as the risk of rare and huge downside events. Statistically, tail events are the possible outcomes placed on the left-tail of distribution. There are three baseline approaches to measure tail risk for aggregate stock markets: one based on option price data, another on high frequency data, and the other on individual stock data. First of all, the option-based approach includes risk-neutral skewness and kurtosis proposed by Bakshi, Kapadia, and Madan (2003). Second, Bollerslev and Todorov (2011) estimate tail risk using high-frequency data. Finally, Kelly and Jiang (2014) measures time-varying tail risk from the cross-section of stock returns. Among them, we select option-implied measure of market tail risk.

There are several reasons to decide to measure market tail risk based on option market data. First, past studies have shown that information in option prices provide valuable forecasts of features of the future payoff distributions in the underlying asset (e.g., Bates, 1991; Jackwerth and Rubinstein, 1996). Bates (1991) argues that option market prices efficiently capture the information and expectation of market participants. In this study, we try to measure the future potential for tail events of stock markets. Thus, options could reflect a true *ex ante* measure of expectation on future return distribution of stock market. Second, the past literature shows significant relationship between market-wide high-moment risks implied by index option and hedge fund returns (Agarwal et al, 2010), and argues that that the negative jump (or tail) risk is sufficiently reflected by the overpricing of deep OTM put options (e.g., Bollen and Whaley, 2004). Thus, it is natural to test hedge fund managers' timing ability with respect to market tail risk reflected in option market. Furthermore, there are data availability issue for high frequency data, restricting high-frequency approach. Also, the hedge fund database suffers from survivorship bias and backfill bias so a standard sample for research generally starts from at least 1994 and our option database is available from 1996. Hence, it is also natural to investigate our research question using combined sample of the both hedge funds and option markets. Finally, tail risk measure proposed by Kelly and Jiang (2014) is implied by the cross-section of individual stock returns. Although they assess that the impact of aggregate firm-level measures from individual stocks could come up with a market-wide measure, their measure is insufficient to capture all the market-wide information regarding tail risk.[5] On the other hand, the option could have its underlying asset as the both individual stock and market index, so the use of the option data available in index options may allow us to measure direct market-wide tail risk.

Our first proxies for option-implied tail risk are risk-neutral moments proposed by Bakshi, Kapadia,

[5] We conduct empirical analysis using Kelly and Jiang (2014) tail risk measure and get similar results but empirical values are weaker than those with tail measure from option data.

and Madan (2003). Agarwal, Bakshi, and Huij (2010) investigate the exposures of hedge fund returns to volatility, skewness, and kurtosis risks implied from the S&P 500 index option prices, and show that some strategies, such as Event Driven and Long Short Equity, exhibit significant exposure to higher moment risks. Bakshi and Madan (2000) show that any payoff of a asset can be built using a set of option prices with different strike prices on that asset. Bakshi, Kapadia, and Madan (2003) describe how to calculate the risk-neutral density moments in terms for quadratic, cubic, and quartic payoffs. They express the τ-maturity of an asset that pays the quadratic, cubic, and quartic return on the base asset as:

$$V(t,\tau) = \int_{S(t)}^{\infty} \frac{2\left(1-\text{h}\left(\frac{K}{S(t)}\right)\right)}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{2\left(1+\text{h}\left(\frac{S(t)}{K}\right)\right)}{K^2} P(t,\tau;K)dK \tag{6}$$

$$W(t,\tau) = \int_{S(t)}^{\infty} \frac{6\,\text{h}\left(\frac{K}{S(t)}\right)-3\left(\text{h}\left(\frac{K}{S(t)}\right)\right)^2}{K^2} C(t,\tau;K)dK - \int_{0}^{S(t)} \frac{6\,\text{h}\left(\frac{S(t)}{K}\right)+3\left(\text{h}\left(\frac{S(t)}{K}\right)\right)^2}{K^2} P(t,\tau;K)dK \tag{7}$$

$$X(t,\tau) = \int_{S(t)}^{\infty} \frac{12\left(\text{h}\left(\frac{K}{S(t)}\right)\right)^2-4\left(\text{h}\left(\frac{K}{S(t)}\right)\right)^3}{K^2} C(t,\tau;K)dK + \int_{0}^{S(t)} \frac{12\left(\text{h}\left(\frac{S(t)}{K}\right)\right)^2+4\left(\text{h}\left(\frac{S(t)}{K}\right)\right)^3}{K^2} P(t,\tau;K)dK \tag{8}$$

where $C(t,\tau;K)$ and $P(t,\tau;K)$ are the prices of European calls and puts written on the underlying asset with strike price K and maturity τ from time t. To empirically estimate the skewness, we need to approximate the integrals in Eq. (6), (7), and (8). We use a trapezoidal approximation to estimate the above integrals using discrete observed option prices data, following Dennis and Mayhew (2002).[6]

Using the prices of these contracts, risk-neutral skewness and kurtosis can be calculated as:

$$SKEW\,(t,\tau) = \frac{e^{r\tau}X(t,\tau)-3\mu(t,\tau)e^{r\tau}V(t,\tau)+2\mu(t,\tau)^3}{[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2]^{\frac{3}{2}}} \tag{9}$$

$$KURT(t,\tau) = \frac{e^{r\tau}X(t,\tau)-4\mu(t,\tau)e^{r\tau}W(t,\tau)+6e^{r\tau}\mu(t,\tau)^2V(t,\tau)-3\mu(t,\tau)^4}{[e^{r\tau}V(t,\tau)-\mu(t,\tau)^2]^2} \tag{10}$$

where r denotes the risk-free rate and $\mu(t,\tau)$ means the risk-neutral expectation of τ-period log returns:

$$\mu(t,\tau) \equiv e^{r\tau} - 1 - \frac{e^{r\tau}}{2}V(t,\tau) - \frac{e^{r\tau}}{6}W(t,\tau) - \frac{e^{r\tau}}{24}X(t,\tau) \tag{11}$$

Second proxies for option-implied tail risk is the slope of the implied volatility smirk for out-of-the-money (OTM) put options. The past literature argue that the negative jump risk is reflected by the overpricing of deep OTM put options and investors' aversion toward negative jumps is the driving force for the volatility smirks. (e.g., Bollen and Whaley, 2004; Xing, Zhang, and Zhao, 2010) Therefore, OTM puts become unusually expensive and volatility smirks become especially prominent before big negative jumps.

We estimate the slope of volatility smirk by calculating regression coefficient using options with

[6] In addition to discrete trapezoidal integrations, we can calculate integral in Eq. (6), (7), and (8) using cubic spline interpolation approach (Chang, Christoffersen, and Jacobs, 2013; DeMiguel, Plyakha, Uppal, and Vilkov, 2013). For each maturity, we interpolate implied volatilities of OTM options inside available moneyness range and extrapolate using the last known value to fill thousand grid points in the given moneyness range. Then we convert these interpolated volatilities into call and put prices to calculate integral. We also use this approach to measure option-implied risk-neutral moments but our main empirical results do not change.

Black-Scholes delta greater than -0.5 and one-month maturity. A steeper and more negative slope of the smirk means that OTM puts are especially expensive relative to ATM puts. We calculate two kinds of the slope of volatility smirk: one with S&P 500 index options and the other with individual stock options. To account for cross-section of individual stock level risk, we add the slopes of volatility smirks for individual stock options.

Data on S&P 500 index options and individual stock options from 1996 to 2012 are obtained from OptionMetrics. We use daily option prices and implied volatilities data to compute the above four kinds of option-implied tail risk measures. First, we calculate risk-neutral skewness (hereafter R.N.Skew) and kurtosis (hereafter R.N.Kurt) of S&P 500 index options using trapezoidal approximation. We only use OTM put and call S&P 500 index options with positive open interest, bid-ask option pairs with non-missing quotes, non-zero bids, and option prices satisfying no-arbitrage conditions. We only estimate the moments for days that have at least two OTM put and call prices available. Secondly, we compute the slope of OTM put implied volatility smirk of S&P 500 index option (hereafter S&P Slope) using OTM put options with positive open interest, non-zero bids, and having delta greater than -0.5. The S&P Slope is estimated from a regression of OTM put-implied volatility on option moneyness, defined as strike over spot. We similarly calculate the slope of implied volatility smirk for all individual stocks in OptionMetrics and construct equal-weighted average across stocks for each day (hereafter Indi Slope). These four measures are estimated separately for two sets of options with maturities closest to 30-day: one set for the maturity higher than 30, and the other set for the maturity lower than 30, then the estimates are linearly interpolated to arrive at a daily measure with constant 30-day maturity. Finally, since hedge fund database has its frequency on monthly level, all daily measures are averaged within the same month to arrive at a monthly time-series.

Panel A of Table 1 reports the correlation matrix of four kinds of option-implied tail risk proxies. First, the correlation between R.N. Skew and R.N. Kurt is -0.92. That is, market is more likely to be leptokurtic or fat-tailed when market is expected to be left-tailed suggesting that fat tail might be caused by downside jumps rather than upside ones. Also, R.N. Skew has positive correlations with S&P Slope and Indi Slope with values 0.55 and 0.40 each and R.N. Kurt has negative correlations with S&P Slope and Indi Slope with values -0.60 and -0.48. These correlations imply that steeper and more negative slope of volatility smirks are associated to lower value of R.N. Skew and higher value of R.N. Kurt. Considering that the steeper slope means potential big negative jumps, these correlation values are reasonable. Finally, S&P Slope and Indi Slope is positively correlated.

To construct single option-implied tail risk measure, we conduct principal component analysis to get a single time-series of monthly option-implied tail risk and estimate the first principal component of the four proxies for market tail risk. For all proxies, rescale the measure to have unit variance and zero mean. The resulting option-implied tail risk is as follows:

$$Op-Tail_{m,t} = -0.553 \cdot R.N.Skew_t + 0.574 \cdot R.N.Kurt_t$$

$$-0.461 \cdot S\&P\ Slope_t - 0.388 \cdot Indi\ Slope_t \quad (12)$$

The first principal component explains 67.31% of the sample variance, and we are convinced that the single principal component captures much of the common variation. This standardized principal component of option-implied tail risk measure (hereafter *Op-Tail*) are plotted in Figure 1 as straight line. Figure 1 also plots the standardized realized market tail after 1-month as dotted line, measured as the daily minimum return within a month, and we can check that increase in *Op-Tail* implied sharp is associated to increase in market downside returns, for example, October 1997 (Asia Crisis) and August 1998 (Collapse of LTCM). Also, *Op-Tail* is fairly persistent, with a monthly AR(1) coefficient is 0.77. Therefore, we focus on innovation or change of *Op-Tail* not the level of *Op-Tail* and subtract the lagged value of *Op-Tail* in the previous month and define $\Delta(Op - Tail)$ as the final option-implied tail risk we focus on. Our final tail risk timing model Eq. (5) becomes as:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\Delta(Op - Tail)_{m,t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1} \quad (13)$$

where $\Delta(Op - Tail)_{m,t+1}$ is the monthly change of $Op - Tail_{m,t}$, computed as the first standardized principal component of four proxies as Eq. (12) and this change value also standardized to have mean zero for ease of interpretation following the de-meaning process of other timing literatures (e.g., Busse, 1999; Cao, Chen, Liang, and Lo, 2013). The other factors are the same as Eq. 5).

Before we conduct empirical examination for hedge fund tail risk timing, we check the properties of our option-implied tail risk measure. We conduct simple regression analysis to figure out the relationship between market portfolio and option-implied risk measure. First, we define the benchmark market portfolios as value-weighted market (noted as VW MKT), equal-weighted market (noted as EW MKT), and S&P 500, then construct monthly *ex-post* characteristics of market portfolios using daily time-series of these market returns; skewness, kurtosis, minimum 1-day returns, and maximum 1-day returns, which are associated to distribution of market portfolios. Then, we conduct monthly regression specified as:

$$Tail(Market)_{t+k} = constant + b_1 * Tail(Market)_t + b_2 * \Delta(Op - Tail)_{m,t} + \varepsilon_{t+k} \quad (14)$$

where $Tail$ is above four proxies for realized market tail and $\Delta(Op - Tail)$ is the option-implied tail risk measure. Panel B in Table 1 summarizes the estimates of b_2, which is loading on option-implied tail risk. First, our option-implied measure of tail risk is significantly associated to contemporaneous market realized tail proxies, such as skewness and minimum return within a month. Also, in terms of skewness of kurtosis, our option-implied measure does not significantly related to the past *ex-post* market tail. However, $\Delta(Op - Tail)$ has significant impact on future market minimum daily return (realized market tail events or market crash). For example, one standard deviation increase of change of option-implied tail is significantly associated to decrease of market downside return of 0.23 times of its standard deviation. On the other hand, $\Delta(Op - Tail)$ does not significantly affect the future market upside return and also sign is negative. Furthermore, our option-implied tail measure is significantly responsive to the past market *ex-post* left and right tails. When market maximum returns increase or minimum return decrease, option-implied measure is getting bigger. Figure 1 plots the time-series of $\Delta(Op - Tail)$ and 1-month ahead of the time-series of minimum daily value-weighted market portfolio within a month, and we can check that the increase in option-implied tail is correlated to decrease in market ex-post left-tail in the near future.

3. The Hedge Fund Data

3 – 1 Hedge Fund Sample

We construct our hedge fund sample from Lipper TASS (hereafter TASS) database, which is one of the most extensive hedge fund data sources and has been widely used for empirical examination of hedge fund literature. The database reports net-of-fee monthly returns, asset under management, and also contains information about a variety of fund characteristics such as lockup, redemption frequency, incentive and management fee rates, inception dates, and investment style.[7] Because TASS database maintains information on defunct funds after 1994 and OptionMetrics has option data starting from 1996, our joint sample starts from 1996, which could mitigate potential survivorship bias of hedge fund database.

During our survivorship bias free sample after 1994, TASS contains a total of 19,370 live and graveyard funds. Among the commonly used fund selection criteria, we filter out funds that have quarterly (not monthly) tracking frequency, funds that report returns before (not after) fees, funds with unknown styles, and funds that do not provide information about a management company in TASS. Also, we include only funds with average assets under management (AUM) of at least $5 million.[8] To control for backfill bias (or incubation bias), we further discard the first 18 months of returns for each fund. We then require each fund to have at least 36 return observations to obtain meaningful estimation results.

TASS classifies hedge funds into eleven self-reported strategy categories: convertible arbitrage, dedicated short bias, emerging markets, equity market neutral, event driven, fixed income arbitrage, global macro, long/short equity, managed futures, multi-strategies, and fund of funds. Since the objective of this study is to investigate hedge fund managers' timing ability for tail risks in stock market, especially implied by option market, we drop the categories including fixed income arbitrage, dedicated short bias, and managed futures to make our sample consist of only equity-oriented funds. Because funds of funds are treated as a separate category, some important analysis are conducted only to the sample without funds of funds (labeled as 'Hedge Funds'). After these filters, our final sample contains

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[7] The database contains information as of the date for which the fund's data are downloaded. Following prior studies, we assume that these information hold throughout the life of the fund.

[8] We do not filter out funds that report returns in currencies other than US dollars. Rather, we use month-end exchange rates to convert them to US dollars. In the process, we lose some return observations (but no fund observations) due to missing exchange rate data. For non-US dollar denominated funds, we use month-end exchange rates to convert their AUM to US dollar values. Our inference remains unchanged when we do not impose AUM filters.

6147 equity-oriented hedge funds over the sample period of 1996-2012, of which 2580 are funds of funds and 3567 are hedge funds in the seven equity-based strategy categories.

Table 2 summarizes the descriptive statistics of monthly return in excess of one-month Treasury bill rate for our sample funds. In Panel A, we find that the hedge fund industry grows steadily from 737 in 1996 to 4503 in 2008 and then declines to 3156 in 2012 after recent global financial crisis. During the sample period, the lowest average monthly return is -2.11% in 2008 financial crisis and the highest average monthly return is 1.84% in 1999. In addition, for better visual understanding, we depict the time series of returns for our sample funds in Figure 2. Panel A of Figure 2 depicts the time-series as equal-weighted monthly excess returns of all funds in our sample and Panel B reports that of sample without funds of funds. Also, we add the time-series of market realized extreme down-side returns, measured by minimum daily value of CRSP value-weighted average returns within a month. The graph shows that hedge funds returns are highly volatile and they also seems to be highly susceptible to market-wide extreme events such as the Russian debt default in 1998 (Collapse of LTCM) and recent global financial crisis in 2008 (Liquidation of hedge funds of Bear Sterns) when the minimum market daily returns show substantial downward spikes in the stock market. The simple time-series average of hedge fund excess returns seem to indicate that hedge funds in aggregate are vulnerable to extreme market conditions and do not display reliable hedging ability with respect to market downturn events despite their purported sophistication.

Panel B reports the summary statistics for portfolios of funds by investment style. The equal-weighted portfolio of all individual funds yields an average monthly excess return of 0.43% (about 5.26% per year) over the sample period, with a standard deviation of 4.76%. Hedge funds show higher average monthly excess return of 0.56% (about 6.90% per year) than funds of funds having average monthly excess returns of 0.26% (about 3.11% per year).[9] Among different hedge fund strategies, emerging markets hedge funds have the highest average monthly return of 0.69%, whereas equity market neutral have the lowest average monthly return of 0.32%. Meanwhile, multi-strategy and equity market neutral exhibit the highest and lowest return volatility respectively. In terms of the number of funds by investment style, sample size ranges from the highest of 2,580 individual funds in fund of funds to the lowest of 138 individual funds in convertible arbitrage. Moreover, the summary statistics of various fund characteristics for our sample funds are displayed in Panel A of Table 3. In our empirical studies, we consider fund characteristics which are commonly discussed in other previous studies, including management fee, incentive fee, whether the fund has a high-water mark, minimum investment amount, whether the fund uses leverage, logarithm of fund age and fund size, lockup period, and redemption

[9] Fung and Hsieh (2000) argues that funds of funds charge investors with operating expenses and management fees on top of the fees charged by underlying hedge funds and often hold some cash or equivalent to meet potential sudden redemption. These two factors may cause this difference in average net of free returns.

notice period (in 30 days). From the results, we confirm that these summary statistics are similar to and comparable with those in the previous hedge fund studies using the TASS database.

3 – 2 Risk Factors

Prior studies have widely documented that hedge funds use dynamic trading strategies and have time-varying systematic risk exposures for other asset classes (Fung and Hsieh, 1997, 2001; Mitchell and Pulvino, 2001; Agarwal and Nail, 2004; Cao, Chen, Liang, and Lo, 2013; Patton and Ramadorai, 2013). In this case, traditional factors based on linear payoffs might not appropriately capture the hedge funds risk-return tradeoff. There, considering the distinct nature of hedge funds, we adopt the widely used nine-factor model as our benchmark when measuring tail-risk timing ability of hedge funds.

Specifically, we first consider the Fung and Hsieh seven-factor model (Fung and Hsieh, 2004), which includes an equity market factor (MKTRF), a size spread factor (SMB), a bond market factor (YLDCHG), a credit spread factor (BAAMTSY), and three trend-following factors for bonds (PTFSB), currency (PTFSFX), and commodities (PTFSCOM). Moreover, we also include Carhart (1997) momentum factor (UMD), and Pastor and Stambaugh (2003) market liquidity factor (LIQ).

Panel B of Table 3 presents the summary statistics of these risk factors. The average market excess return, our main variable of interest, is 0.46% (about 5.71% per year) per month over 1996–2012 with a standard deviation of 4.76%. During the sample period, the two worst-performing market returns are –16.08% (August 1998) and –17.23% (October 2008) within a month, when the hedge fund index also performs badly and in those periods many individual hedge funds record tremendous losses.

4. Empirical Results

In this section, we first discuss the cross-sectional distribution of t-statistics for the option-implied tail risk timing coefficients across individual hedge funds. We then further conduct a bootstrap analysis to assure the statistical significance of the timing ability of hedge funds. Moreover, we show that option-implied tail risk timing skill reflects a valuable managerial skill and is directly associated to superior future fund performance and its significance and persistency. Furthermore, we find evidence suggesting that the option-implied tail risk timing skill is persistent over time.

4-1 Cross-Sectional Distribution of t-Statistics for Tail Risk Timing

To investigate whether hedge funds managers possess option-implied tail risk timing skill, we first estimate the timing skill using regression Eq. (13) for individual hedge funds in our sample. To draw a meaningful inference from the regression coefficients, we require each fund to have at least 36 monthly observations of time-series of returns. Before conduct empirical analysis for individual funds, we run a regression Eq. (13) of the average returns of all funds in our sample. With the average returns using the sample including all funds and the sample excluding funds of funds, we get the estimated timing coefficients of -0.025 (t-statistic = -0.81) and -0.032 (t-statistic = -1.07) respectively. Thus, we can conclude that hedge funds do not show significant timing ability on average.

Table 4 reports the results of the cross-sectional distribution of t-statistics for tail risk timing coefficients estimated from Eq. (13) across individual funds. In particular, the table reports the percentage of individual funds exceeding several specified conventional critical values (1%, 2.5%, 5%, and 10% significance levels) under normality assumption. Since market tail risk get bigger as our tail measure increases and we are trying to focus on the tail risk timing ability of hedge fund managers, our main interest is the left tails of estimated cross-sectional distribution of t-statistics. For instance, 8.95% of our sample funds have t-statistics smaller than -1.96 and 5.68% of funds have t-statistics smaller than -2.326, whereas 2.73% of the funds have t-statistics greater than 1.96 and 1.17% of funds have t-statistics bigger than 2.326, suggesting that some funds display negative tail risk timing, i.e., some funds unusually tend to increase its exposure to market when the market tail risk turns out to be high. For the overall sample, the left tails exhibit thicker than the right tails, suggesting that there are more hedge funds reducing their exposure to market when tail risk appear high than otherwise. In addition, we check the same analysis for funds in each strategy category. From Table 4, we find that almost all the categories have thicker left tails and the hedge funds categorized in event driven and convertible arbitrage have more significant positive tail risk timing than others.

Overall results indicate that there exist hedge fund managers displaying the significant tail risk timing skill according to the conventional critical values under the normality assumption. However, as dicussed by Cao, Chen, Liang, and Lo (2013), above results based on the statistical inference under the conventional normality assumption have to be interpreted with caution when we are dealing with a sample of hedge funds. More specifically, it is well documented that due to their dynamic trading strategies (e.g., Fung and Hsieh, 1997) or usage of derivatives (e.g., Chen, 2011), hedge fund returns generally do not follow normal distributions. In addition, when we evaluate managerial skill using the extensive number of funds, some funds truly having no true timing skill appear to have significant t-statistics by chance. Thus, when we want to evaluate managerial skills from a large sample of hedge funds, one of the most important point we need to consider is to distinguish managerial skill from pure luck. In this regard, we further implement a bootstrap analysis to check whether those estimated timing coefficients are attributed to either true managerial skill or pure luck in the following subsection.

4-2 Bootstrap Analysis

In this subsection, we describe the bootstrap procedure for assessing the statistical significance of option-implied tail risk timing coefficients for individual hedge funds. The bootstrap analysis will be of help to address the question of whether a positive (or negative) estimation result for tail risk timing skill comes from true managerial skill or pure luck. For each cross-sectional t-statistic of the timing coefficient, we compare the actual estimate with the corresponding cross-sectional t-statistics from the distribution of estimates based on bootstrapped pseudo-funds that have no timing skill, and then, we determine whether observed significant tail risk timing skill can be explained by random sampling variation. Because the t-statistic is a pivotal statistic and has favorable sampling properties, whereas the coefficient estimator is not (e.g., Horowitz, 2001; Cao, Chen, Liang, and Lo, 2013), we conduct the bootstrap analysis using t-statistics (i.e., t_γ) instead of the timing coefficients (i.e., γ). Specifically, our bootstrap analysis is similar to that of Kosowski, Timmermann, White, and Wermers (2006), Chen and Liang (2007), Fama and French (2010), and Cao, Chen, Liang, and Lo (2013). The basic process of the bootstrap analysis is that we first randomly resample data (e.g., regression residuals of returns from our timing model Eq. (13)) to generate hypothetical funds that, by construction, have the same factor loadings as the actual funds but have no timing ability, setting the timing coefficient to be zero. Then we examine statistically whether the t-statistics of estimated timing coefficients for the actual funds are different from the bootstrapped hypothetical distribution extracted from randomly generated hypothetical funds having no timing skill. Our detailed bootstrap procedure has following five steps:

1. Estimate the option-implied tail risk timing model for fund p:

   $$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\Delta(Op - Tail\ )_{m,t+1} + \sum_{j=1}^{J}\beta_j f_{j,t+1} + \varepsilon_{p,t+1} \quad (15)$$

   and store the estimated coefficients $\{\widehat{\alpha_p},\ \widehat{\beta_p},\ \widehat{\gamma_p}, \ldots\}$ as well as the time-series of residuals $\{\hat{\varepsilon}_{p,t+1}$, t: 0, …, $T_p - 1\}$, where T_p is the number of monthly observations for fund p.
2. Resample the residuals with replacement and obtain a randomly resampled residual time-series $\{\hat{\varepsilon}^n_{p,t+1}\}$, where *n* is the index of bootstrap iteration ($n = 1,2, \ldots, N$). Then, generate monthly excess returns for a pseudo-fund having no tail risk timing skill. That is, construct return series setting the coefficient of option-implied tail risk timing to be zero, i.e., $\gamma_p = 0$ or, equivalently, $t_\gamma = 0$, for each fund as follows:

   $$r^n_{p,t+1} = \hat{\alpha}_p + \hat{\beta}_p MKT_{t+1} + \sum_{j=1}^{J}\hat{\beta}_j f_{j,t+1} + \hat{\varepsilon}^n_{p,t+1} \quad (16)$$
3. Estimate the option-implied tail risk timing model Eq. (15) using the resampled pseudo-fund returns from Step 2, and store the estimate of the new timing coefficient and its t-statistic. Because the pseudo-fund has a true γ of zero by construction, non-zero timing coefficient (and t-statistic) comes from sampling variation.
4. Complete Steps 1-3 across all the sample funds, so that the cross-sectional statistics of the estimates of the timing coefficients and their t-statistics across all of the sample funds can be observed. For example, we compute the top 1% percentile of t-statistics from the sample of pseudo-fund returns then compare with original top 1% percentile from our hedge fund samples to get the bootstrapped p-value.
5. Repeat Step 1-4 for N iterations to generate the empirical distributions for cross-sectional statistics (e.g., the top 1th percentile) of t-statistics for the pseudo-funds. In our analysis, we repeat the overall steps 3000 times. Finally, for a given cross-sectional statistics, calculate its bootstrapped empirical

p-value as the proportion that the values of the cross-sectional statistic (e.g., the top 1th percentile) for the pseudo-funds from 3000 simulations exceed the actual value of the cross-sectional statistic.

For each different extreme percentile (1%, 3%, 5%, and 10%) of t-statistics of tail risk timing coefficients, Table 5 reports the empirical p-values from bootstrap analysis. This p-value test the hypothesis that the significant tail risk timing coefficients of hedge funds are attributed to pure luck. In the same manner as Table 4, we focus our interpretation on the results of left-tail (positive tail risk timing). For the whole our sample, all the empirical p-value of extreme percentiles (from 1% to 10%) suggests that the top timing funds are unlikely to be attributed to random chance. Specifically, for the sample of 6,147 funds, the actual t-statistics for the top 1%, 3%, 5%, and 10% tail risk timing funds are -3.43, -2.78, -2.41, and -1.87, respectively, with empirical p-values all close to zero.

In addition, we also conduct a bootstrap analysis for funds in each strategy category. We find low empirical p-values for the top-ranked funds in the following strategies: fund of funds, convertible arbitrage, event driven, global macro, and long-short equity, indicating the notion that top-ranked funds' tail risk timing coefficients for the above strategy categories are not due to random chance. However, the timing coefficients of top-ranked funds in the emerging markets, equity market neutral, and multi-strategy strategies cannot be distinguished from pure luck coming from sampling variation. On the other hand, the timing coefficients of negative tail risk timing funds, located in the right-tail of the distribution of timing coefficients, are might be due to random chance except for one strategy category; long-short equity.

In summary, the evidence from the bootstrap analysis suggests that top-ranked hedge fund managers can time market tail risk, and the results for negative timing coefficients cannot be attributed to random chance. For more clear investigation about whether tail risk timing truly captures valuable managerial skill, we further examine the economic value of tail risk timing skill to fund investors.

4-3 Economic Value of Tail Risk Timing

In this subsection, we examine whether tail risk timing skill of hedge fund managers add economic value to investors. If the tail risk timing represents critical managerial skill, then the funds timing well on the market tail risk might perform well in the future and tail risk timing measure helps predict future fund performance. Thus, assuming that the tail risk timing represents valuable managerial skill, we conduct two kinds of analysis to figure our economic significance of tail risk timing; univariate portfolio-level analysis and multivariate Fama-MacBeth (1973) cross-sectional analysis.

We start by analyzing the relationship of tail risk timing and hedge fund returns using univariate portfolio sorts. In each month starting from January 1996, we estimate the tail risk timing coefficient for each fund having at least 18 non-missing value of net-of-free fund returns over the past 24-month estimation period by the tail risk timing model Eq. (13). Then we construct ten equal-weighted portfolios by sorting individual hedge funds based on their tail risk timing coefficient, where decile 1 contains the hedge funds with the highest timing skill (top timers) and decile 10 contains the hedge funds with the lowest timing skill (bottom timers). These portfolios are held subsequently for a three-, six-, nine-, and twelve-month holding period, and we repeat this process.[10] Next we calculate the average monthly excess returns and then evaluate the risk-adjusted performance for each of the ten portfolios by regressing their monthly portfolio returns on the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity risk factor.[11]

Table 6 reports both the average monthly excess returns and nine-factor alphas for decile tail risk timing sorted portfolios, as well as a long-short portfolio that is long the top timer portfolio and short the bottom timer portfolio over the four kinds of s holding periods. Since sometimes funds of funds are treated as a separate category (e.g., Cao et al., 2013), we conduct univariate portfolio analysis only with the sample containing other categories except for funds of funds. Panel A shows the result with all funds and Panel B reports the results with hedge funds except for funds of funds. Throughout the portfolio analysis, we find the economic value of tail-risk timing of hedge funds on the future superior performance. In Table 6, the long-short spread in the excess returns between top (portfolio 1) and bottom (portfolio 10) timers is 0.35% per month (4.32% per year) for three-month holding period (t-statistic = 1.80). After controlling for the other risk factors, the risk-adjusted spread between top and bottom timers is still remarkable, both economically and statistically, at 0.41% per month (5.09% per year) with a t-statistic of 2.30, suggesting that the economic value of hedge funds created from tail risk timing remain significant after controlling for well-known risk factors.

Table 6 also reports the performance of tail risk timing sorted portfolios for the longer holding periods. As shown in Panel A of Table 6, for the other holding periods from six to twelve months, funds in the highest timing skill decile consistently outperform those in the lowest decile and the differences are both economically and statistically significant for all cases, and the average long-short spreads between top and bottom timers are 0.43%, 0.49%, and 0.50% (5.23%, 6.10%, and 6.11% per year, respectively) for six, nine, and twelve-month holding periods. As in the three-month holding period case, the difference in subsequent performance after adjusting for the nine factors exhibit even larger both in magnitude and statistical significance. For instance, for a 12-month holding periods, the risk-adjusted spread is 0.55% per month (6.84% per year). That is, top tail risk timing funds outperform bottom timers about by 5% - 7% per year subsequently on risk-adjusted basis. This outperformance of top timer than bottom timer and monotonicity of subsequent performance is also shown in the only hedge fund sample without funds of funds. The results are shown in Panel B of Table 6.

[10] We decide the minimum holding period as three-month due to the average lock-up period for our sample funds is close to three-month (actually 76 days).

[11] We include momentum and liquidity factor because our baseline model is 9-factor as in Eq. (13). For robustness, our results do not change when we alter our baseline model as Fung and Hsieh (2004) seven-factor.

The economic value of tail risk timing can be seen more directly from Figure 3. We additionally check the full visualized distribution of performance of decile portfolios. Figure 3 plot out-of-sample alphas of decile hedge fund portfolio within the both whole sample and the sample without funds of funds for 12-month holding periods. The out-of-sample alphas of 12-month holding periods monotonically increase as tail risk timing skill reduces. Moreover, Figure 4 plots out-of-sample alphas for the portfolios of top versus bottom timing funds across different holding periods. Figure 4 shows that for three-month holding case, top tail risk timing funds exhibit an average alpha four to five times as large as that of bottom timing funds, and this difference increases as holding periods get longer.

So far, we investigate the relationship between tail risk timing skill and future hedge fund performance using the univariate portfolio-level analysis. However, the portfolio-level analysis is difficult to control for other factors simultaneously. Meanwhile, existing literature have suggested several hedge fund characteristics that are known to affect future performance. Thus, we run the Fama-MacBeth (1973) regressions of monthly hedge fund excess returns or alphas on funds' timing skill, simultaneously controlling for fund characteristics and investment styles to get a clear inference about the economic value of tail risk timing of hedge funds.

We first calculate monthly risk-adjusted return relative to the Fung-Hsieh (2004) seven factors, the Cahart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor for each hedge fund with at least 24 months return observations. We then run the cross-sectional regression for the average of monthly hedge fund excess returns or alphas for different holding periods. To fit the empirical format of univariate portfolio analysis, we calculate time-series moving average of monthly excess returns and alphas for from three- to twelve-month of all individual hedge funds and run following specified regressions:

$$Excess_{i,t} \text{ or } Alpha_{i,t} = \alpha + \beta\, Timing\ Beta_{i,t-1} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{17}$$

where $Timing\ Beta_{i,t-1}$ is a tail risk timing coefficient of fund *i* for month t-1 estimated from timing model Eq. (13) using past 24-month rolling estimation window. The $X_{i,t-1}$ represents various fund characteristics including log of fund age, log of asset under management (AUM), management fee, incentive fee, the high-water mark dummy, minimum investment, lockup period, and redemption notice period, and investment strategy dummies.

Table 7 summarizes the results of the Fama-MacBeth (1973) cross-sectional regression for the full sample period January 1996 January to December 2012. Consistent with our earlier findings from the univariate portfolio analyses, in both univariate (with timing skill as the only independent variable) and multivariate regressions, with either fund excess return or alpha as the dependent variable, regression results provide evidence of a negative and significant relation between timing skill and future fund returns. In details, the univariate coefficient of timing skill ranges from -0.0029 to -0.0041 with significant t-statistics across different holding periods. The results with fund alpha are similar and economic significance increases. Furthermore, the results of multivariate analysis shows that the tail risk timing skill of hedge funds still remain significant predictor of future excess returns or 9-factor alphas across different holding periods even after controlling for various fund characteristics and strategy dummy simultaneously. Additionally, the overall coefficients of fund characteristics are consistent with prior literature. For example, funds with high-watermark, funds with higher minimum investment amount, younger and smaller funds, and funds with longer restriction periods tend to have better performance.

To sum up, our overall results from portfolio analysis and cross-sectional regressions indicate that tail risk timing skill of hedge fund managers adds economic value to investors, and therefore the tail risk timing skill reflects crucial managerial skill for hedge funds and can be one of the important sources for hedge fund alpha. We also show that this timing skill persists over time in out-of-sample testing. The results is consistent with previous literature which documents that hedge fund alphas significantly persists over time (e.g., Jaganathan, Malakhov, and Novikov, 2010; Cao, Chen, Liang, and Lo, 2013). Finally, economic value of tail risk timing of hedge funds are robust to other fund characteristics which may affect future performance and hedge funds. In the next subsection, we simply check the persistency of tail risk timing ability of hedge funds.

4-4 Persistence of tail risk timing

Now, to further confirm our results that tail risk timing skill reflects true managerial skill, we investigate whether this skill persists over time in out-of-sample tests. In the similar spirit of portfolio analysis, we form decile portfolios based on the past tail risk timing coefficients estimated from the option-implied tail risk timing model Eq. (13). Then we calculate post twelve-month tail-risk timing coefficient using the same timing model Eq. (13) and show the simple average of those post timing coefficient within decile portfolios.

Figure 5 presents the results of portfolio's post-formation timing skill for a 12-month holding period. From the results, we find strong evidence of persistence in tail risk timing skill for top-ranked hedge funds. For example, the portfolio consisting of the top 10% timing funds (top timers) in the past 24 months reveals an average of out-of-sample timing coefficient of -0.081 for a 12-month post-formation period, while the bottom 10% timing funds (bottom timers) has a subsequent timing coefficient of -0.014 for the same period. The spread between timing coefficient of top and bottom timers is 0.068 and it is statistically significant at the 1% level. Also, post-formation timing coefficients exhibit a monotonic pattern from deciles from portfolio 1 (top timer) to portfolio 10 (bottom timer), suggesting that top (bottom) timers, who reduce their market exposure effectively (ineffectively) when market tail risk turns out to be high, persist their behaviors to perform well (worse) in the future. This results is also consistent with the past hedge fund literature which documents that outperformance of hedge funds persists over time. To summarize, our evidence implies that tail risk timing skill persists over time in out-of-sample tests, and is also consistent with the prior results showing that the tail risk timing skill does not come from pure luck but from superior managerial skill.

5. Additional Results and Robustness

In this section, we investigate the robustness of our results to alternative explanations. We first conduct additional tests whether a specified group of hedge funds sample cause biases to our main inferences about tail risk timing ability. In details, there is possibility that our results on tail risk timing might be driven by usage of leverage and redemption constraints or by the impact of large funds' trading on overall market conditions, such as market tail risk. Also, we conduct sub-period analysis by excluding the 2008-2009 global financial crisis period. Furthermore, we are concerned about the possibility that other managerial skills or timing ability could affect the tail risk timing of hedge funds. Therefore, we control for other timing skills and well-known managerial skills to prove that the tail risk timing is robust to other potential factors.

5-1 Subsample Analysis

This subsection tests the sample biases which might affect the inference on tail risk timing. First, as noted by Lo (2008), usage of leverage through short-term funding exposes funds to the risk of sudden margin calls that can force them to liquidate positions. Such forced liquidations also happen to many funds simultaneously, especially during the market shocks when market tail risk becomes high. Thus, one might wonder whether the reduction of market exposure under sudden market shock or increase of market tail risk merely reflects responses to a deterioration of funding liquidity because prime brokers cut funding or increase borrowing costs. Hence, we repeat our analysis using a subsample of funds that do not use any leverage or use leverage. If the changes in funds' market exposure to sudden shift of market tail risk are caused by fluctuation of leverage not by managerial skill, then funds that do not use leverage should not show significant tail risk timing ability and their cross-sectional difference of superior performance.

Secondly, apart from broker-dictated changes in leverage, external funding constraints can also be caused by investors' redemptions. Similar mechanism to changes in leverage, changes in funds' market exposure can be merely caused by funding constraints due to investors' redemption. This is because fund managers need to unwind their positions and decrease their market exposure when investors withdraw their capitals (e.g., Khandani and Lo, 2007). For example, during the recent global financial crisis, many hedge funds experienced heavy investors' redemption suddenly and some funds were forced to liquidate their positions. Therefore, we repeat our analysis using funds that impose a redemption frequency of one quarter or longer and funds that require redemption notice period of 60 days or longer. A longer redemption frequency blocks sudden investors' redemptions and this provision is especially effective during extreme market conditions such as high tail risk market. Also, a longer redemption notice period allows fund managers to have more time to adjust positions to meet sudden investors' withdrawal and this provision is also reduce funding constraints due to an impact of investors' redemption. In this regard, we concerns about the possibility that changes in funds' market exposures are responses to investors' redemptions not by managerial skill. Hence, we need to test whether hedge funds with lower redemption frequency exhibit weak tail risk timing ability. If fund managers reduce their market beta because of redemptions, funds with loose redemption pressure should not show significant tail risk timing ability.

Finally, we consider the impact of large funds' trading on overall market conditions. For instance, if large funds liquidate their positions, especially equity, simultaneously within a month, market conditions could extremely deteriorate for the next periods, which could generate a positive link between fund market exposure and subsequent market tail events. Because of this possibility, we investigate tail risk timing ability of small funds because trading activities of small funds are more unlikely to affect market conditions than others. To do so, we classify funds into small funds if its total asset under management (AUM) is less than \$50 million or \$150 million. If the changes of funds' market exposure are caused by the trading activity of large hedge funds, hedge funds with small AUM should display weak evidence of tail risk timing.

Table 8 reports the bootstrap analysis for six kinds of subsamples: funds that use leverage or not, that have redemption frequency equal or greater than a quarter, that impose redemption notice period equal or longer than 60 days, and that have assets under management (AUM) below \$50 or \$150 million. For brevity, we only reports the results of bootstrap analyses for all funds, hedge funds (sample without funds of funds), and funds of funds.[12] Overall results in Table 8 suggest that regardless of usage of leverage, whether redemption frequency is low or not, and fund size, all subsamples shows the significant tail risk timing and their timing ability is not attributed to pure luck. All the p-values on the columns named as bottom t-statistics for timing skill are close to zero. Although external leverage and investors' redemption can affect funds' market exposure, they do not reflect managerial skill. Also, our results are not driven by large funds' trading that could have impact on market conditions.

Furthermore, we conduct the simple univariate portfolio analysis using six subsamples. To conserve the space, we only reports 12-month holding period 9-factor alphas of decile portfolio based on the funds' tail risk timing coefficients and the difference between top and bottom timers. The results of subsample portfolio analysis are summarized in Table 9. All six subsamples show economically and statistically significant alphas for top-timer portfolio and the difference between top and bottom timers are also significant. This results add the robustness for our results arguing that tail risk timing is one of the important managerial skills. In summary, none of our findings qualitatively change when we conduct various alternative subsample analyses, suggesting that our main inferences on the tail risk timing ability of hedge funds are mostly dictated from managers' superior timing skill, not from changes in

[12] The details of results are available upon request.

leverage, sudden investors' redemption requests, or trading impact of large funds.

5-2 Sub-Period Analysis

In this subsection, we first test whether the main findings discussed in previous parts remains consistent during subsample periods. The main reason for various subsample analyses in the previous subsection is associated to market crises because fluctuation of leverage, funding constraints like investors' redemption, and large trade of funds are the greatest during the periods of market crises. Our main results are drawn from the full sample period from January 1996 to December 2012, there may be concern that results could be driven by specific short periods such as 2008-2009 financial crisis periods when extreme market tail events occurred. Hence, to alleviate the concern and confirm the robustness of our results, we repeat our main analysis using the sub-sample of pre-crisis periods (January 1996 to December 2007). We mainly check whether the tail risk timing skill of hedge funds still exits and this skill adds economic value to investors.

Panel A of Table 10 reports the empirical results for bootstrap analysis with sample of pre-crisis periods. Consistent with Table 5, we reports actual t-statistics of timing coefficients at different extreme percentiles (from 1% to 10%) and corresponding empirical p-values calculated from bootstrap analysis. The overall results show that top-ranked hedge funds have their empirical p-values close to zero as in Table 5, suggesting that the tail risk timing ability of top-ranked hedge funds are unlikely to be attributed to random chance or pure luck. Also, we report the results of univariate portfolio analysis as Table 6. Panel B of Table 10 reports the average performance of decile equal-weighted hedge fund portfolios for the pre-crisis periods. We display both the average monthly excess returns and nine-factor alphas for each portfolio as well as a long-short spread between top and bottom timers and we check the performance of portfolios over the various holding periods (from three to twelve months). As shown in Panel B of Table 10, we can easily confirm that average monthly holding period returns as well as risk-adjusted returns decrease monotonically from portfolio 1 (top timer) to portfolio 10 (bottom timer), and the long-short spread is highly significant for almost all holding horizons. In summary, the results in Table 10 indicate that our inferences on the tail risk timing by hedge funds still remain unchanged even after excluding the 2008-2009 financial crisis periods from our sample and that it can be evidence that our main findings are not driven by sample bias.

5-3 Controlling for Other Timing Skills

In our main analyses, our base-line timing model mainly focuses on the strategical adjustment of market exposure according to option-implied market tail risk to investigate the existence of market tail risk timing ability of hedge fund managers. However, the previous studies have documented that fund managers time market returns, volatility, and liquidity as well. Moreover, it is well documented that market tail risk is highly correlated with other aspects of market. For instance, market tail risk is likely to be positively correlated with market volatility and negatively correlated with market returns and market liquidity. Under these circumstance, our empirical findings about option-implied tail risk timing of hedge fund managers could be driven by other dimensions of managers' timing ability. For example, if managers adjust their market exposure in response to other dimensions of market such as liquidity or volatility and simultaneously changes of market tail risk implied by options, then those managers appear to time option-implied market tail risk but do not actually possess tail risk timing ability. Hence, to confirm that our empirical results are not driven by correlations between our tail risk measures and other market conditions, we first explicitly control for other dimensions of timing skill in our base-line option-implied tail risk timing model as a following specification:

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1} \Delta(Op-Tail)_{m,t+1} + \lambda_p MKT_{t+1}^2 + \delta_p MKT_{t+1}\left(Vol_{t+1} - \overline{Vol}\right) + \theta_p MKT_{t+1}\left(Liq_{t+1} - \overline{Liq}\right) + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1} \quad (18)$$

where Vol_{t+1} is the market volatility in month t+1 as measured by the CBOE S&P 500 index option implied volatility (i.e., the VIX) and $\overline{Vol}$ is the time series mean of market volatility. Liq_{t+1} is Pastor-Stambaugh (2003) market-liquidity measure and $\overline{Liq}$ is the time series mean of the liquidity measure. In our specification, the coefficients γ, $\boldsymbol{\lambda}$, $\boldsymbol{\delta}$, and $\boldsymbol{\theta}$ measure tail risk timing, market return timing, volatility timing, and liquidity timing, respectively. Using the extended timing model Eq. (18), we estimates the tail risk timing coefficients for each hedge fund and conduct bootstrap analysis to confirm the existence of tail risk timing skill and portfolio analysis to check the economic value of tail risk timing skill after control for other timing aspects..

Panel A of Table 11 reports the results of bootstrap analysis for the extended timing model Eq. (18) including actual t-statistics of timing coefficients for funds in each category and corresponding empirical p-values at different cross-sectional percentiles calculated from bootstrap analysis. For all funds sample, $t_{\hat{\gamma}}$ for the top 1%, 3%, 5%, and 10% of option-implied tail risk timing funds are -3.29, -2.54, -2.18, and -1.65, respectively, and their empirical p-values are close to zero. This results also hold for all hedge funds sample except for funds of funds and some strategy categories such as convertible arbitrage, event driven, and long-short equity. Furthermore, Panel B of Table 11 presents the results of out-of-sample performance of tail risk timing sorted portfolios over various holding periods. The out-of-sample performance suggests that tail risk timing ability of hedge funds has economic value to investors significantly after controlling for other dimensions of timing skills. Interestingly, the average monthly excess return spread and difference in alphas between top and bottom timers becomes stronger than before. In summary, overall results in Table 11 suggest that our inferences about our main findings of significant evidence of tail risk timing ability remain unchanged.

Furthermore, we conduct double sorting analysis to confirm whether the economic value driven by tail risk timing is robust after controlling for other timing ability. First, we use our baseline model, Eq. (5), to estimate market returns, market volatility, and liquidity timing ability for individual fund. We modify Eq. (5) changing tail risk into market returns, market volatility or liquidity and we use CBOE S&P 500 index option implied volatility (i.e., the VIX) and Pastor-Stambaugh (2003) market liquidity measure to proxy for market volatility and liquidity respectively. Then, at the beginning of each month, we independently sort all funds into quintile portfolios based on estimated option implied tail risk timing coefficients and tercile portfolios based on estimated market timing, market volatility timing, or liquidity timing coefficients. For each market, volatility, or liquidity timing group, we check the monthly average future alphas for each tail risk timing portfolio and the spread between top and bottom timers for different holding periods, 3- to 12-month. Table 12 summarizes the results of two-way portfolio analysis. To conserve the space, we only report the results of nine portfolios among fifteen (5 by 3) portfolios and the difference between top and bottom timers. For example, in the first three columns of Panel D of Table 12 (i.e., liquidity timing control and 12-month holding periods case), the spreads between top timer (Portfolio1) and bottom timer (Portfolio 5) for option implied tail risk are 0.31%, 0.27%, and 0.35% for three liquidity timing groups respectively after controlling for nine-factor and these spreads are all statistically and economically significant. Except for some cases, all the spreads of alphas are statistically significant, so we conclude that the tail risk timing ability of hedge funds adds economic value to investors even after controlling for timing ability to other aspects of stock market, implying that tail risk timing is crucial managerial skills of hedge fund managers determining future performance of funds.

5-4 Controlling for Other Managerial Skills

So far, we try to explore a new dimension of hedge fund managers' skill; ability to time market tail risk implied by option market, and argue that this skill brings significant economic value to investors. Meanwhile, academics and practitioners have long been interested in investigating hedge funds' managerial skill and have suggested various measures as a proxy for the skills. In this regards, we need to check whether our timing skill indeed exhibits a distinctive aspect of managerial skills compared to other existing managerial skill proxies. To confirm this point, we consider two well-documented managerial skill proxies, which are highly related to our tail risk timing skill; hedging ability of fund managers proposed by Titman and Tiu (2011) and fund performance in down market suggested by Sun, Wang, and Zheng (2014).

At first, Titman and Tiu (2011) argue that skilled hedge fund managers will reduce the exposure to systematic risk and therefore their fund returns will exhibit a lower R-squared with respect to the systematic risk factors, such as Fung and Hsieh (2004) seven factors, and find significant empirical evidence for their argument. Since funds with low R-squared tend to have better managers' ability of hedging against systematic risk, those funds more likely to have better skill for timing market tail risk. Thus, one might concerns that tail risk timing of hedge fund managers is driven by managers' hedging ability proxied by R-square.

Secondly, Sun, Wang, and Zheng (2014) document that hedge fund performance is persistent only periods of relative hedge fund market weakness, and find significant evidence implying that the hedge fund performance over the down market is more informative about managerial skills and hence better predictor of future performance. Thus, these authors suggest hedge fund performance measure, named as '*Downside-Returns*' to proxy the fund performance when aggregate funds perform badly. Since the periods when aggregate hedge funds performs badly overlap the periods of higher market tail risk, we additionally test whether our tail risk timing measure are robust to performance measure proposed by Sun, Wang, and Zheng (2014).

To do this robustness test, first we measure two other managerial skills. For each fund, R-square (*RSQ)* is measured by rolling r-square from a regression of excess returns of hedge funds on Fung and Hsieh (2004) seven factors using an estimation periods of two years, and we measure *RSQ* only for funds having at least 18 non-missing return series. To measure *Downside-Returns*, we first identify the 12 months over which the aggregate hedge fund returns are below the median level over the past 24-month window, then for each hedge fund with at least 6 observations over the 12 months, we take the time-series average of fund returns to get the *Downside-Returns* measure as follows:

$$\textit{Downside-Returns}_i = \frac{1}{T_i}\sum_{t=1}^{T_i} r_{i,t}\, |r_{HF,t} \text{ below 50 percentile} \quad (19)$$

After constructing those measures of managerial skills, *RSQ* and *Downside-Returns*, we examine whether the predictive power of tail risk timing skill for future hedge funds performance still remains even after controlling for other two managerial skill proxies. We conduct the following Fama-MacBeth (1973) cross-sectional regression by including both the tail risk timing skill (*Timing Beta*) and the aforementioned two skill proxies:

$$Excess_{i,t} \text{ or } Alpha_{i,t} = \alpha + \beta\, Timing\ Beta_{i,t-1} + \gamma' OtherSkill_{i,t-1} + \delta' X_{i,t-1} + \varepsilon_{i,t} \quad (20)$$

Where $OtherSkill_{i,t-1}$ includes *RSQ* and *Downside-Returns*, and $X_{i,t-1}$ represents various fund characteristics and investment strategy dummies as in Eq (17).

Results are reported in Table 13. To conserve the space, we only report the estimation results for the coefficient of *Timing Beta*, *RSQ*, and *Downside-Returns*. Panel A reports the results of cross-sectional regression with independent variables of only three managerial skill without characteristics control over the different holding periods and Panel B reports those with funds' characteristics control. Throughout the results, our tail risk timing skill still remains economically and statistically significant. Also, in terms of alphas, *RSQ* and *Downside-Returns* have significant predictive ability for future hedge fund performance as the previous studies documented. To sum up, overall results in Table 13 suggest that our tail risk timing skill of hedge fund has strong economic meaning for managerial skill and is robust to other managerial skill proxies, which are likely to be associated to the tail risk timing ability.

6. Conclusions

In this paper, we examine whether hedge funds, among the most professional and sophisticated asset managers, have market tail risk timing ability. The previous literature has focused on fund managers' timing ability on market returns, and some studies documented timing ability on market volatility and liquidity. However, we first try to propose the timing ability of hedge fund managers on a new unexplored dimension of market dimension, which is market tail risk. Since market tail risk has critically affected the performance of many hedge funds, we focus on market tail risk as our market condition of interest.

First, we measure market tail risk based on the information extracted from option markets because it has been well-known that option price contains information about the contemporaneous state and future payoff distributions in the underlying asset. Using the market-wide tail risk calculated from option price data and an extensive sample of sample of equity-oriented hedge funds from 1996 to 2012, we find significant evidence suggesting that there exists positive tail risk timing ability among hedge fund managers. That is, hedge fund managers strategically increase (decrease) their market exposures when market tail risk is expected to be high (low). Furthermore, we confirm that our results cannot be attributed to pure luck or multi-sample bias by conducting bootstrap analysis.

Moreover, we find evidence suggesting that top timer hedge funds bring economic value to investors through various out-of-sample tests. Specifically, using the whole sample, the funds in the highest tail risk timing decile outperform the funds in the lowest decile by approximately 5% - 7% per year subsequently on risk-adjusted basis across various holding periods. Also, we show that tail risk timing ability of hedge funds persists over time. Finally, various additional tests show that our main inferences are robust to alternative analyses including subsample analysis, sub-period analysis, and the use of controls for other market dimensions of timing ability and other types of hedge fund managerial skills. Overall, our findings contributes to the academic literature on the managerial skills of hedge funds, especially timing ability, and emphasize the importance of incorporating market tail risk in their investment decisions for practitioners and investors.

References

Admati, A.R., Bhattacharya, S., Pfleiderer, P., Ross, S.A., 1986. On timing and selectivity. Journal of Finance 41, 715-730.

Agarwal, V., Bakshi, G., Huij, J. 2010. Do higher-moment equity risks explain hedge fund returns? Unpublished working paper.

Agarwal, V., Naik, N., 2004. Risks and portfolio decisions involving hedge funds. Review of Financial Studies 17, 63-98.

Bakshi, G., Kapadia, N., Madan, D., 2003. Stock return characteristics, skew laws, and the differential pricing of individual equity options. Review of Financial Studies, 16(1), 101-143.

Bakshi, G., Madan, D., 2000. Spanning and derivative-security valuation. Journal of Financial Economics, 55(2), 205-238.

Bates, D. S., 1991. The crash of'87: Was it expected? The evidence from options markets. Fournal of Finance, 46(3), 1009-1044.

Becker, C., Ferson, W., Myers, D.H., Schill, M.J., 1999. Conditional market timing with benchmark investors. Journal of Financial Economics 2, 119-148.

Bodnaruk, A., Chokaev, B., Simonov, A., 2015. Downside risk timing by mutual funds. Unpublished working paper.

Bollen, N.P.B., Busse, J.A., 2001. On the timing ability of mutual fund managers. Journal of Finance 56, 1075-1094.

Bollen, N. P., Whaley, R. E., 2004. Does net buying pressure affect the shape of implied volatility functions?. The Journal of Finance, 59(2), 711-753.

Bollerslev, T., Todorov, V., 2011. Tails, fears, and risk premia. Journal of Finance, 66(6), 2165-2211.

Brown, S., Goetzmann, W., Ibbotson, R., 1999. Offshore hedge funds: survival and performance 1989-95. Journal of Business 72, 91-117.

Busse, J., 1999. Volatility timing in mutual funds: evidence from daily returns. Review of Financial Studies 12, 1009-1041.

Carhart, M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57-82.

Cao, C., Chen, Y., Liang, B., Lo, A.W., 2013. Can hedge funds time market liquidity? Journal of Financial Economics 109, 493-516.

Chang, B. Y., Christoffersen, P., Jacobs, K., 2013. Market skewness risk and the cross section of stock returns. Journal of Financial Economics, 107(1), 46-68.

Chang, E.C., Lewellen, W.G., 1984. Market timing and mutual fund investment performance. Journal of Business 51, 57-72.

Chen, Y., 2007. Timing ability in the focus market of hedge funds. Journal of Investment Management 5, 66-98.

Chen, Y., 2011. Derivatives use and risk taking: Evidence from the hedge fund industry. Journal of Financial and Quantitative Analysis, 46(04), 1073-1106.

Chen, Y., Ferson, W., Peters, H., 2010. Measuring the timing ability and performance of bond mutual funds. Journal of Financial Economics 98, 72-89.

Chen, Y., Han, B., Pan, J., 2016. Sentiment Risk, Sentiment Timing, and Hedge Fund Returns. Unpublished working paper.

Chen, Y., Liang, B., 2007. Do market timing hedge funds time the market? Journal of Financial and Quantitative Analysis 42, 827-856.

DeMiguel, V., Plyakha, Y., Uppal, R., Vilkov, G., 2013. Improving Portfolio Selection Using Option-Implied Volatility and Skewness. Journal of Financial and Quantitative Analysis, 48(06), 1813-1845.

Dennis, P., Mayhew, S., 2002. Risk-neutral skewness: Evidence from stock options. Journal of Financial and Quantitative Analysis, 37(03), 471-493.

Fama, E., 1972. Components of investment performance. Journal of Finance, 27, 551-567.

Fama, E., MacBeth, J., 1973. Risk, return and equilibrium: empirical tests. Journal of Political Economy 81, 607-636.

Ferson, W.E., Schadt, R.W., 1996. Measuring fund strategy and performance in changing economic conditions. Journal of Finance 51, 425-460.

Fung, W., Hsieh, D.A., 1997, Empirical characteristics of dynamic trading strategies: the case of hedge funds. Review of Financial Studies 10, 275-302.
Fung, W., Hsieh, D. A., 2000. Performance characteristics of hedge funds and commodity funds: Natural vs. spurious biases. Journal of Financial and Quantitative analysis, 35(03), 291-307.
Fung, W., Hsieh, D.A., 2001. The risk in hedge fund strategies: theory and evidence from trend followers. Review of Financial Studies 14, 313-341.
Fung. W., Hsieh, D.A., 2004. Hedge fund benchmarks: a risk-based approach. Financial Analysts Journal 60, 65-80.
Fung, W., Hsieh, D.A., Naik, N., Ramadorai, T., 2008. Hedge funds: Performance, risk, and capital formation. Journal of Finance 63, 1777-1803.
Goetzmann, W.N., Ingersoll, J., Ivkovich, Z., 2000. Monthly measurement of daily timers. Journal of Financial and Quantitative Analysis 35, 257-290.
Grinblatt, M., Titman, S., 1989. Portfolio performance evaluation: old issues and new insights. Review of Financial Studies 2, 393-421.
Henriksson, R., 1984. Market timing and mutual fund performance: an empirical investigation. Journal of Business 57, 73-96.
Henriksson, R., Merton, R., 1981. On market timing and investment performance II: statistical procedures for evaluating forecasting skills. Journal of Business 54, 513-534.
Hong, Y., Tu, J., Zhou, G., 2007. Asymmetries in stock returns: statistical tests and economic evaluation, Review of Financial Studies 20, 1547-1581.
Horowitz, J. L., 2001. The bootstrap. Handbook of econometrics, 5, 3159-3228.
Jackwerth, J. C., Rubinstein, M., 1996. Recovering probability distributions from option prices. Journal of Finance, 51(5), 1611-1631.
Jagannathan, R., Korajczyk, R., 1986. Assessing the market timing performance of managed portfolios. Journal of Business 59, 217-245.
Jagannathan, R., Malakhov, A., Novikov, D., 2010. Do hot hands exist among hedge fund managers? An empirical evaluation. Journal of Finance 65, 217-255.
Jensen, M.C., 1972. Optimal utilization of market forecasts and the evaluation of investment performance. Mathematical Methods in Finance. North-Holland.
Jiang, W., 2003. A nonparametric test of market timing. Journal of Empirical Finance 10, 399-425.
Jiang G.J., Yao, T., Yu, T., 2007. Do mutual funds time the market? Evidence from portfolio holdings. Journal of Financial Economics 86, 724-758.
Kelly, B., Jiang, H., 2012. Tail risk and hedge fund returns. Unpublished working paper.
Kelly, B., Jiang, H., 2014. Tail risk and asset prices. Review of Financial Studies 27, 2841-2871.
Khandani, A., Lo, A., 2007. What happened to the quants in august 2007?(digest summary). Journal of Investment Management, 5(4), 29-78.
Kosowski, R., Timmermann, A., Wermers, R., White, H., 2006. Can mutual fund “stars” really pick stocks? New evidence from a bootstrap analysis. Journal of Finance 61, 2551-2595.
Lo, A. W., 2008. Hedge funds, systemic risk, and the financial crisis of 2007-2008: written testimony for the House Oversight Committee hearing on hedge funds. Unpublished working paper.
Merton, R., 1981. On market timing and investment performance I: an equilibrium theory of value for market forecasts. Journal of Business 54, 363-407.
Mitchell, M., Pulvino, T., 2001. Characteristics of risk and return in risk arbitrage. Journal of Finance 56, 2135-2175.
Pastor, L., Stambaugh, R. F., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642-685.
Patton, A.J., Ramadorai, T., 2013. On the high-frequency dynamics of hedge fund risk exposures. Journal of Finance 68, 597-635.
Shanken, J., 1990. Intertemporal asset pricing: An empirical investigation. Journal of Econometrics, 45(1-2), 99-120.
Stulz, R. M., 2007. Hedge funds: Past, present, and future. Journal of Economic Perspectives, 21(2), 175-194.

Sun, Z., Wang, A.W., Zheng, L., 2014. Hedge fund performance persistence over different market conditions. Unpublished working paper.
Titman, S., Tiu, C., 2011. Do the best hedge funds hedge? Review of Financial Studies 24, 123-168.
Treynor, J., Mazuy, K., 1966. Can mutual funds outgess the market? Harvard Business Review 44, 131-136.
Xing, Y., Zhang, X., Zhao, R., 2010. What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns? Journal of Financial and Quantitative Analysis, 45(3), 641-662.

Table 1. Correlation Matrix of Option-Implied Measures and the Relationship between Market Portfolio and Option-Implied Tail Risk Measure

This table presents correlation matrix of four option-implied measures; risk-neutral skewness (R.N. Skew), risk-neutral kurtosis (R.N. Kurt), the slope of the implied volatility smirk for out-of-the-money S&P 500 put options (S&P Slope), and the equally weighted average of the slopes of implied volatility smirk for out-of-the-money put options of individual stocks (Indi Slope) and the relationship between the characteristics of market portfolio and the option-implied tail risk measure (Op-Tail). Panel A reports the Pearson correlation matrix of above four measures. The details on the construction and description of these four option-implied measures and Op-Tail are described in Section 2-2. Panel B reports the estimates of monthly regression results of the characteristics of market portfolio on the change of the Op-Tail. We conduct monthly regression $\mathrm{Tail}\,(\mathrm{Market})_{t+k} = constant + b_1 * Tail\ (Market)_t + b_2 * \Delta(Op - Tail)_{m,t} + e_{t+k}$ where 'Tail' is realized skewness, kurtosis, minimum and maximum daily market returns. These four kinds of market realized tail are calculated in every month using daily realized market-returns series. Also, 'Market' is value (or equal)-weighted aggregate stock market or returns of S&P 500 index. When k is equal to zero, we regress realized market on the only constant and contemporaneous$\Delta(Op - Tail)$. We only reports estimated b_2 coefficients for each k from -4 to 4 and Newey-West (1987) t-statistics using twelve months of lags. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

Panel A. Correlation Matrix

	R.N.Skew	R.N.Kurt	S&P Slope	Indi Slope
R.N.Skew	1.00			
R.N.Kurt	-0.92	1.00		
S&P Slope	0.55	-0.60	1.00	
Indi Slope	0.40	-0.48	0.35	1.00

Panel B. Regression on Market Realized Tail

k	**-4**	**-3**	**-2**	**-1**	**0**	**1**	**2**	**3**	**4**
Skew (VW MKT)	**0.12***	-0.05	-0.03	**0.12***	**-0.08****	-0.02	-0.07	-0.01	0.01
	(1.85)	(-0.82)	(-0.50)	**(1.94)**	**(-1.98)**	(-0.38)	(-1.14)	(-0.18)	(0.13)
Skew (EW MKT)	**0.15****	-0.01	0.02	0.04	**-0.13*****	0.04	-0.08	-0.08	0.07
	(2.23)	(-0.17)	(0.23)	(0.59)	**(-2.72)**	(0.61)	(-1.15)	(-1.29)	(1.01)
Skew (S&P 500)	0.09	-0.05	-0.04	**0.13****	**-0.08***	-0.04	-0.07	0.00	-0.02
	(1.42)	(-0.81)	(-0.57)	**(2.07)**	**(-1.90)**	(-0.55)	(-1.09)	(-0.07)	(-0.35)
Kurt (VW MKT)	-0.09	**-0.38****	0.11	0.02	0.14	-0.07	0.17	-0.11	-0.21
	(-0.60)	**(-2.49)**	(0.68)	(0.16)	(1.36)	(-0.44)	(1.17)	(-0.72)	(-1.41)
Kurt (EW MKT)	-0.25	-0.18	0.02	-0.01	0.06	-0.11	0.16	-0.08	-0.16
	(-1.36)	(-0.97)	(0.11)	(-0.07)	(0.46)	(-0.60)	(0.95)	(-0.50)	(-0.98)
Kurt (S&P 500)	-0.07	**-0.41*****	0.11	0.05	0.16	-0.04	0.23	-0.14	**-0.27***
	(-0.45)	**(-2.64)**	(0.71)	(0.29)	(1.47)	(-0.26)	(1.51)	(-0.95)	**(-1.76)**
MIN (VW MKT)	-0.05	**-0.26***	**-0.44*****	**-0.46*****	**-0.37****	**-0.22***	**-0.26***	0.07	-0.14
	(-0.33)	**(-1.88)**	**(-3.35)**	**(-3.76)**	**(-2.52)**	**(-1.78)**	**(-1.94)**	(0.50)	(-0.96)
MIN (EW MKT)	0.03	-0.20	**-0.37*****	**-0.45*****	**-0.33****	**-0.25****	-0.21	0.00	-0.12
	(0.21)	(-1.54)	**(-2.95)**	**(-3.94)**	**(-2.41)**	**(-2.08)**	(-1.65)	(-0.03)	(-0.85)
MIN (S&P 500)	-0.06	**-0.26***	**-0.44*****	**-0.44*****	**-0.37*****	**-0.23***	**-0.25***	0.09	-0.17
	(-0.43)	**(-1.88)**	**(-3.32)**	**(-3.61)**	**(2.54)**	**(-1.82)**	**(-1.87)**	(0.63)	(-1.15)
MAX (VW MKT)	0.02	0.11	0.20	**0.39*****	-0.13	-0.12	0.10	-0.15	-0.07
	(0.15)	(0.84)	(1.63)	**(3.68)**	(-0.93)	(-1.06)	(0.85)	(-1.20)	(-0.56)
MAX (EW MKT)	0.06	0.11	**0.20***	**0.37*****	-0.14	0.01	0.14	-0.16	-0.02
	(0.54)	(1.00)	**(1.79)**	**(3.92)**	(-1.11)	(0.10)	(1.29)	(-1.44)	(-0.19)
MAX (S&P 500)	0.03	0.11	0.20	**0.41*****	-0.12	-0.11	0.11	-0.15	-0.08
	(0.21)	(0.82)	(1.62)	**(3.78)**	(-0.90)	(-1.03)	(0.87)	(-1.16)	(-0.58)

Table 2. Summary Statistics for Hedge Funds Monthly Excess Returns

This table presents descriptive statistics of monthly fund excess returns (in excess of one-month T-bill rate) for our sample hedge funds. Panel A summarize several descriptive statistics, including number of funds, mean, standard deviation, and various percentiles, of monthly fund excess returns across years, and Panel B summarizes descriptive statistics of monthly fund excess returns across fund strategies. The returns are in percent. The sample period is from January 1996 to December 2012.

Year	# of Funds	Mean	Median	Std.Dev	P25	P75
Panel A. Average Fund Returns by Year						
1996	737	1.043	0.850	3.917	-0.400	2.404
1997	923	0.908	0.750	4.594	-0.830	2.700
1998	1140	-0.130	0.362	6.788	-1.860	2.400
1999	1326	1.839	0.820	7.771	-0.760	3.290
2000	1564	0.212	0.222	6.503	-2.162	2.137
2001	1837	0.102	0.210	4.635	-1.199	1.490
2002	2158	0.115	0.236	4.242	-1.110	1.460
2003	2575	1.645	0.989	3.547	0.020	2.723
2004	3055	0.823	0.580	2.839	-0.434	1.940
2005	3622	0.332	0.360	3.125	-1.209	1.670
2006	3990	0.856	0.623	3.107	-0.661	2.142
2007	4365	0.833	0.660	3.343	-0.663	2.190
2008	4503	-2.114	-1.065	6.613	-4.713	1.367
2009	4409	1.786	1.261	5.150	-0.296	3.372
2010	4016	0.649	0.696	4.458	-1.359	2.900
2011	3616	-0.463	-0.099	4.795	-2.334	1.700
2012	3158	0.428	0.619	3.929	-0.850	2.130
Panel B. Average Fund Returns by Strategy						
All Funds	6147	0.428	0.500	4.757	-1.156	2.190
Hedge Funds	3567	0.558	0.560	5.214	-1.210	2.482
Fund of Funds	2580	0.255	0.430	4.062	-1.098	1.867
Convertible Arbitrage	138	0.330	0.440	4.010	-0.410	1.320
Emerging Markets	373	0.693	0.681	7.221	-1.711	3.366
Equity Market Neutral	234	0.319	0.339	4.020	-0.850	1.690
Event Driven	393	0.490	0.510	3.449	-0.420	1.610
Global Macro	217	0.549	0.422	5.061	-1.534	2.580
Long/Short Equity Hedge	1498	0.570	0.537	5.474	-1.640	2.840
Multi-Strategy	714	0.639	0.800	4.825	-0.930	2.743

Table 3. Summary Statistics for the Hedge Fund Characteristics and Risk Factors

This table summarizes various fund characteristics and risk factors used in our empirical analyses. Panel A reports summary statistics of fund characteristics. Fund characteristics include management fee, incentive fee, the high-water mark dummy, minimum investment, the leverage usage dummy, log of fund age, log of fund size (log of AUM), lockup period, and redemption notice period in month. Panel B presents the Fung-Hsieh (2004) seven factors, namely excess market returns (MKTRF), size factor (SMB), monthly change in the ten-year Treasury constant maturity yield (YLDCH), monthly change in the Moody's Baa yield less ten-year Treasury constant maturity yield (BAAMT), and three trend following factors on bonds (PTFSB), foreign exchange (PTFSFX), and commodity (PTFSCOM), as well as the Carhart (1997) momentum factor (UMD), and the Pastor-Stambaugh (2003) liquidity factor (LIQ). The sample period is from January 1996 to December 2012.

Character	Mean	Median	Std.Dev	P25	P75
Panel A. Summary of Fund Characteristics					
Mfee	1.39	1.50	0.64	1.00	1.75
Ifee	13.08	20.00	8.48	5.00	20.00
Highwatermarkt	0.53	1.00	0.50	0.00	1.00
Mininv	0.74	0.25	2.43	0.05	1.00
Leverage	0.53	1.00	0.50	0.00	1.00
Age	4.12	4.13	0.61	3.69	4.56
AUM	17.79	17.75	1.55	16.74	18.82
Lockup	2.60	0.00	6.34	0.00	0.00
Notice	1.14	1.00	1.05	0.17	1.50
Panel B. Summayr of Risk Factors					
MKTRF	0.46	1.18	4.76	-2.33	3.50
SMB	0.23	0.00	3.67	-1.93	2.47
UMD	0.43	0.60	5.69	-1.39	3.17
YLDCH	-0.01	-0.03	0.22	-0.13	0.09
BAAMT	-0.02	-0.04	0.23	-0.16	0.13
PTFSB	-1.93	-4.53	15.11	-13.16	3.40
PTFSFX	-0.34	-4.22	18.57	-13.69	9.19
PTFSCOM	-0.02	-2.72	13.96	-9.01	7.09
LIQ	0.77	0.40	4.18	-1.29	3.12

Table 4. Cross-Sectional Distribution of t-Statistics of the Tail Risk Timing Coefficients

This table reports the cross-sectional distribution of t-statistics of the tail risk timing coefficient for all funds and each strategy categories. Category 'Hedge Funds' contain all funds except for those included in 'Fund of Funds'. In this table, we report the percentage of individual funds exceeding indicated conventional critical values of t-statistics under normality assumption. For funds with at least 24 monthly observations, we estimate following tail risk timing model

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\Delta(Op-Tail)_{m,t+1} + \sum_{j=1}^{J}\beta_j f_{j,t+1} + \varepsilon_{p,t+1}$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1. MKT_{t+1} is the excess return on the market portfolio in month t+1. $\Delta(\mathrm{Op}-Tail)_{t+1}$ is the monthly change of option-implied tail risk measure in month t+1 described in Section 2-2. $f_{j,t+1}$ includes Fung-Hsieh (2004) seven factors and Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. In this specification, the coefficient γ_p captures tail risk timing ability of hedge fund managers. The t statistics are heteroscedasticity consistent. The sample period is from January 1996 to December 2012.

		Percentage of the Funds							
Strategy Category	# of Funds	t ≤ -2.326	t ≤ -1.960	t ≤ -1.645	t ≤ -1.282	t ≥ 1.282	t ≥ 1.645	t ≥ 1.960	t ≥ 2.326
All Funds	6147	5.68	8.95	12.4	18.29	11.44	5.53	2.73	1.17
Hedge Funds	3567	6.03	9.11	12.53	18.33	12.11	6.17	3.2	1.37
Fund of Funds	2580	5.19	8.72	12.21	18.22	10.5	4.65	2.09	0.89
Convertible Arbitrage	138	13.77	18.12	21.74	28.26	5.07	1.45	0	0
Emerging Markets	373	2.14	6.17	8.58	15.28	13.4	5.63	3.22	1.34
Equity Market Neutral	234	5.13	8.97	12.82	17.95	11.54	6.84	2.14	1.28
Event Driven	393	15.27	20.61	25.95	35.62	9.16	5.85	4.07	1.53
Global Macro	217	5.53	6.45	7.83	10.6	6.91	2.76	1.38	0.92
Long/Short Equity	1498	5.61	8.48	12.68	19.16	10.95	6.28	3.4	1.67
Multi-Strategy	714	2.8	4.76	6.44	9.24	18.63	8.12	3.78	1.12

Table 5. Bootstrap Analysis of Tail Risk Timing Coefficients

This table displays the results of bootstrap simulation of tail risk timing. Details on the procedure of bootstrap analysis are presented in Section 2-2. In this table, for all and each strategy, we report the t-statistics of tail risk timing coefficients estimated from actual fund returns for indicated cross-sectional statistics (e.g., 1,3,5, and 10th percentile) and also present the corresponding empirical p-values from bootstrap simulations. The number of iterations for empirical distribution of t-statistics is 3,000. The sample period is from January 1996 to December 2012.

			Bottom t-Statistics for Timing skill				Top t-Statistics for Timing skill			
Strategy Category	# of Funds		1%	3%	5%	10%	10%	5%	3%	1%
All Funds	6147	t-Stat	-3.43	-2.78	-2.41	-1.87	1.37	1.69	1.93	2.41
		p-Value	0.00	0.00	0.00	0.00	0.00	0.54	0.91	0.99
Hedge Funds	3567	t-Stat	-3.49	-2.83	-2.43	-1.89	1.40	1.73	1.98	2.56
		p-Value	0.00	0.00	0.00	0.00	0.00	0.05	0.21	0.18
Fund of Funds	2580	t-Stat	-3.30	-2.70	-2.36	-1.84	1.32	1.61	1.82	2.27
		p-Value	0.00	0.11	0.00	0.00	0.31	0.99	1.00	1.00
Convertible Arbitrage	138	t-Stat	-3.41	-3.37	-3.01	-2.47	1.02	1.47	1.51	1.66
		p-Value	0.04	0.00	0.00	0.00	1.00	0.97	0.99	1.00
Emerging Markets	373	t-Stat	-3.13	-2.22	-2.04	-1.49	1.43	1.73	1.97	2.72
		p-Value	0.18	0.96	0.43	0.78	0.06	0.42	0.49	0.28
Equity Market Neutral	234	t-Stat	-2.87	-2.46	-2.33	-1.85	1.40	1.76	1.93	2.60
		p-Value	0.23	0.13	0.01	0.00	0.23	0.44	0.58	0.39
Event Driven	393	t-Stat	-4.13	-3.48	-3.27	-2.63	1.21	1.80	2.08	2.92
		p-Value	0.00	0.00	0.00	0.00	0.99	0.70	0.69	0.29
Global Macro	217	t-Stat	-4.20	-3.26	-3.13	-1.39	1.12	1.49	1.64	1.97
		p-Value	0.00	0.00	0.00	0.53	0.85	0.84	0.91	0.92
Long/Short Equity	1498	t-Stat	-3.28	-2.72	-2.36	-1.86	1.35	1.76	2.01	2.61
		p-Value	0.00	0.01	0.00	0.00	0.00	0.01	0.05	0.05
Multi-Strategy	714	t-Stat	-3.20	-2.26	-1.94	-1.17	1.57	1.84	2.06	2.36
		p-Value	0.00	1.00	0.54	1.00	0.00	0.00	0.04	0.59

Table 6. Economic Value of Tail Risk Timing – Portfolio Analysis

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds constructed based on the funds' tail risk timing skill. In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate tail risk timing coefficient and construct equal-weighted decile portfolios that are rebalanced each month according to the estimated coefficients. Portfolios are then held for different holding periods, i.e. 3-, 6-, 9-, and 12-month. For each portfolio and top-minus-bottom timer spread, we report both the monthly excess returns and nine-factor alphas (in percent), including Fung-Hsieh (2004) seven factors and Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor, across different holding periods. Alpha is defined as returns net of what attributable to factor exposures. That is, the alpha is estimated by regression of decile portfolio returns on the Fung-Hsieh (2004) seven factors. Panel A reports the results of portfolio analysis containing all Funds and Panel B presents the results without Fund of Funds. The t-statistics based on Newey-West (1987) standard errors with three lags are in the parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Excess Returns				9-factor Alphas			
	K = 3	6	9	12	K = 3	6	9	12
Panel A. All Funds								
Portfolio1 (Top Timer)	0.70	0.72	0.75	0.74	0.52	0.53	0.57	0.55
	(2.10)	(2.28)	(2.42)	(2.45)	(3.02)	(3.36)	(3.66)	(3.78)
Portfolio2	0.52	0.54	0.61	0.63	0.37	0.40	0.44	0.44
	(2.05)	(2.25)	(2.69)	(2.76)	(2.94)	(3.36)	(3.54)	(3.52)
Portfolio3	0.59	0.55	0.55	0.56	0.39	0.37	0.38	0.38
	(2.60)	(2.71)	(2.78)	(2.73)	(2.36)	(2.67)	(2.88)	(2.66)
Portfolio4	0.32	0.40	0.39	0.37	0.19	0.26	0.27	0.25
	(1.70)	(2.27)	(2.23)	(2.08)	(1.96)	(2.66)	(2.95)	(2.78)
Portfolio5	0.40	0.37	0.35	0.33	0.24	0.23	0.22	0.21
	(2.23)	(2.11)	(1.94)	(1.83)	(2.11)	(2.33)	(2.24)	(2.18)
Portfolio6	0.32	0.35	0.32	0.31	0.21	0.22	0.20	0.19
	(1.77)	(2.01)	(1.81)	(1.71)	(2.05)	(2.12)	(1.96)	(1.90)
Portfolio7	0.29	0.28	0.27	0.27	0.17	0.16	0.15	0.15
	(1.52)	(1.46)	(1.40)	(1.40)	(1.51)	(1.42)	(1.31)	(1.32)
Portfolio8	0.30	0.27	0.26	0.27	0.17	0.13	0.11	0.12
	(1.43)	(1.23)	(1.18)	(1.24)	(1.29)	(0.95)	(0.81)	(0.91)
Portfolio9	0.34	0.30	0.27	0.28	0.19	0.14	0.11	0.11
	(1.49)	(1.25)	(1.15)	(1.18)	(1.34)	(0.96)	(0.75)	(0.80)
Portfolio10 (Bottom Timer)	0.35	0.29	0.25	0.24	0.11	0.06	0.02	0.00
	(1.07)	(0.90)	(0.78)	(0.74)	(0.52)	(0.30)	(0.07)	(0.01)
Portfolio1 - Portfolio10	**0.35***	**0.43****	**0.49*****	**0.50*****	**0.41****	**0.47*****	**0.55*****	**0.55*****
	(1.80)	**(2.54)**	**(3.08)**	**(3.32)**	**(2.30)**	**(2.94)**	**(3.43)**	**(3.66)**
Panel B. Hedge Funds								
Portfolio1 (Top Timer)	0.77	0.80	0.82	0.79	0.58	0.60	0.62	0.60
	(2.06)	(2.26)	(2.36)	(2.37)	(2.94)	(3.33)	(3.55)	(3.69)
Portfolio2	0.60	0.62	0.71	0.70	0.43	0.45	0.51	0.51
	(2.14)	(2.30)	(2.75)	(2.72)	(3.30)	(3.71)	(3.87)	(4.04)
Portfolio3	0.69	0.70	0.72	0.72	0.48	0.49	0.50	0.50
	(2.76)	(2.87)	(2.92)	(2.94)	(2.77)	(2.91)	(2.94)	(2.94)
Portfolio4	0.74	0.60	0.62	0.66	0.47	0.40	0.41	0.44
	(2.23)	(2.70)	(2.73)	(2.56)	(1.82)	(2.58)	(2.59)	(2.25)
Portfolio5	0.40	0.51	0.47	0.44	0.28	0.35	0.33	0.30
	(2.20)	(2.87)	(2.73)	(2.51)	(3.33)	(3.28)	(3.62)	(3.52)
Portfolio6	0.40	0.48	0.43	0.42	0.28	0.33	0.30	0.29
	(2.29)	(2.77)	(2.51)	(2.40)	(3.29)	(2.97)	(3.01)	(3.03)
Portfolio7	0.39	0.38	0.36	0.35	0.26	0.25	0.23	0.22
	(2.12)	(2.05)	(1.90)	(1.85)	(2.70)	(2.66)	(2.41)	(2.36)
Portfolio8	0.43	0.37	0.35	0.36	0.26	0.20	0.18	0.19
	(2.11)	(1.76)	(1.69)	(1.71)	(2.35)	(1.81)	(1.60)	(1.72)
Portfolio9	0.42	0.39	0.37	0.38	0.23	0.19	0.17	0.17
	(1.71)	(1.54)	(1.49)	(1.51)	(1.73)	(1.43)	(1.30)	(1.33)
Portfolio10 (Bottom Timer)	0.42	0.36	0.31	0.31	0.14	0.09	0.03	0.02
	(1.15)	(0.98)	(0.84)	(0.81)	(0.61)	(0.41)	(0.15)	(0.10)
Portfolio1 - Portfolio10	**0.36**	**0.44****	**0.50*****	**0.49*****	**0.44****	**0.51*****	**0.59*****	**0.57*****
	(1.60)	**(2.29)**	**(2.72)**	**(2.83)**	**(2.03)**	**(2.61)**	**(3.01)**	**(3.11)**

Table 7. Economic Value of Tail Risk Timing – Fama-MacBeth Cross-Sectional Regressions

This table reports results from Fama-MacBeth (1973) cross-sectional regressions of hedge fund excess return, as well as alpha for different holding periods, i.e., 3-, 6-, 9-, and 12-month, on funds' tail risk timing beta with controls of fund characteristics and strategy dummies. In each month, for each fund with at least 18 monthly observations in the past 24 months, tail risk timing beta is estimated by regressing the fund's excess returns on the market index and its interaction with tail risk measure, with controls of the Fung-Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor-Stambaugh (2003) liquidity factor. Then, we conduct Fama-Macbeth cross-sectional regressions of average of hedge fund excess returns, as well as alphas for different holding periods, on the tail risk timing beta after controlling for fund characteristics and strategy dummies across different holding periods. Fund characteristics include high-water mark dummy (1 if a high-water mark provision is used and 0 otherwise), incentive fee, management fee, minimum investment, log of fund age, log of fund size (log of AUM), lockup period, and redemption notice period. The t-statistics are based on Newey-West (1987) standard errors with three lags. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Dependent Variable							
	Excess Returns				9-Factor Alphas			
Variable	K = 3	6	9	12	K = 3	6	9	12
Panel A. Univariate Analysis								
Intercept	0.0040**	0.0037**	0.0038***	0.0040***	0.0026***	0.0026***	0.0028***	0.0030***
	(2.27)	(2.40)	(2.84)	(3.53)	(2.89)	(3.42)	(4.21)	(5.11)
Timing Beta	**-0.0029***	**-0.0038*****	**-0.0041*****	**-0.0039*****	**-0.0039*****	**-0.0042*****	**-0.0041*****	**-0.0037*****
	(-1.80)	**(-2.96)**	**(-4.06)**	**(-4.67)**	**(-3.46)**	**(-4.30)**	**(-5.20)**	**(-5.65)**
Strategy Dummy	No	No	No	No	No	No	No	No
Adj-R^2	0.022	0.028	0.028	0.025	0.021	0.026	0.026	0.025
# of Obs	388,975	370,571	352,189	333,824	388,975	370,571	352,189	333,824
Panel B. Multivariate Analysis								
Intercept	0.0162***	0.0171***	0.0160***	0.0153***	0.0126***	0.0142***	0.0132***	0.0124***
	(3.79)	(4.10)	(4.52)	(4.94)	(2.79)	(3.13)	(3.27)	(3.44)
Timing Beta	**-0.0017**	**-0.0024****	**-0.0025*****	**-0.0024*****	**-0.0022****	**-0.0027*****	**-0.0025*****	**-0.0022*****
	(-1.30)	**(-2.43)**	**(-3.19)**	**(-3.43)**	**(-2.30)**	**(-3.22)**	**(-3.76)**	**(-3.84)**
Highwatermark	0.0008**	0.0008**	0.0008**	0.0008**	0.0009***	0.0009***	0.0009***	0.0009***
	(2.22)	(2.38)	(2.44)	(2.51)	(2.63)	(2.94)	(2.96)	(2.96)
Ifee	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000*	0.0000	0.0000**
	(0.73)	(1.19)	(1.46)	(1.57)	(1.21)	(1.78)	(2.11)	(2.27)
Mfee	0.0005	0.0004	0.0005	0.0005*	0.0004	0.0004	0.0005**	0.0005***
	(1.24)	(1.36)	(1.67)	(1.93)	(1.50)	(1.55)	(2.05)	(2.62)
Mininv	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(2.69)	(3.35)	(3.72)	(4.09)	(2.86)	(3.17)	(3.72)	(4.05)
Age	-0.0009**	-0.0008**	-0.0006**	-0.0005*	-0.0013***	-0.0013***	-0.0011***	-0.0010***
	(-2.43)	(-2.47)	(-2.07)	(-1.89)	(-2.96)	(-3.28)	(-3.23)	(-3.32)
AUM	-0.0005**	-0.0006***	-0.0006***	-0.0006***	-0.0003	-0.0003**	-0.0003**	-0.0003***
	(-2.25)	(-3.15)	(-3.88)	(-4.34)	(-1.62)	(-2.19)	(-2.56)	(-2.72)
Lockup	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.51)	(0.40)	(0.54)	(0.66)	(0.53)	(0.45)	(0.58)	(0.72)
Notice	0.0004*	0.0004**	0.0004***	0.0004***	0.0004**	0.0005***	0.0005***	0.0005***
	(1.70)	(2.20)	(2.72)	(3.36)	(2.21)	(2.76)	(3.17)	(3.74)
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.108	0.119	0.125	0.128	0.079	0.092	0.098	0.102
# of Obs	272,649	258,523	244,067	229,574	272,649	258,523	244,067	229,574

Table 8. Fund Leverage, Investor Redemptions, Fund Size, and Tail Risk Timing

This table reports the subsample analysis for the cross-sectional distribution of t-statistics of the tail risk timing coefficient for funds that use leverage or not, that have redemption frequency equal or greater than a quarter, that impose redemption notice period equal or longer than 60 days, and that have assets under management (AUM) below \$50 or \$150 million. Category 'Hedge Funds' contain all funds except for those included in 'Fund of Funds'. In this table, we report the percentage of individual funds exceeding indicated conventional critical values of t-statistics under normality assumption. For funds with at least 24 monthly observations, we estimate following tail risk timing model

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\Delta(Op-TaIl)_{m,t+1} + \sum_{j=1}^{J}\beta_j f_{j,t+1} + \varepsilon_{p,t+1}$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1. MKT_{t+1} is the excess return on the market portfolio in month t+1. $\Delta(Op-TaIl)_{m,t+1}$ is the monthly change of option-implied tail risk measure in month t+1 described in Section 2-2. $f_{j,t+1}$ includes Fung-Hsieh (2004) seven factors and Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. In this specification, the coefficient γ_p captures tail risk timing ability of hedge fund managers. The t statistics are heteroscedasticity consistent. The sample period is from January 1996 to December 2012.

			Bottom t-Statistics for Timing skill				Top t-Statistics for Timing skill			
Strategy Category	# of Funds		1%	3%	5%	10%	10%	5%	3%	1%
Panel A. Bootstrap Analysis for funds that do not use leverage										
All Funds	2892	t-Stat	-3.37	-2.72	-2.38	-1.83	1.35	1.66	1.91	2.45
		p-Value	0.00	0.00	0.00	0.00	0.32	0.90	0.91	0.86
Hedge Funds	1392	t-Stat	-3.30	-2.70	-2.36	-1.80	1.35	1.70	1.95	2.62
		p-Value	0.00	0.00	0.00	0.00	0.44	0.70	0.75	0.44
Fund of Funds	1500	t-Stat	-3.46	-2.74	-2.39	-1.89	1.35	1.63	1.86	2.29
		p-Value	0.00	0.00	0.00	0.00	0.30	0.89	0.92	0.98
Panel B. Bootstrap Analysis for funds that use leverage										
All Funds	3255	t-Stat	-3.48	-2.82	-2.42	-1.88	1.38	1.72	1.95	2.41
		p-Value	0.00	0.00	0.00	0.00	0.03	0.29	0.47	0.82
Hedge Funds	2175	t-Stat	-3.54	-2.86	-2.51	-1.93	1.44	1.74	2.00	2.49
		p-Value	0.00	0.00	0.00	0.00	0.00	0.29	0.31	0.56
Fund of Funds	1080	t-Stat	-3.19	-2.69	-2.29	-1.80	1.25	1.60	1.79	2.15
		p-Value	0.00	0.00	0.00	0.00	0.73	0.78	0.90	0.97
Panel C. Bootstrap Analysis for funds that have redemption frequency equal or greater than a quarter										
All Funds	2082	t-Stat	-3.60	-3.02	-2.73	-2.23	1.13	1.54	1.77	2.20
		p-Value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Hedge Funds	1352	t-Stat	-3.63	-3.00	-2.71	-2.21	1.06	1.54	1.81	2.20
		p-Value	0.00	0.00	0.00	0.00	1.00	0.99	0.96	0.99
Fund of Funds	730	t-Stat	-3.57	-3.12	-2.81	-2.29	1.23	1.56	1.74	2.14
		p-Value	0.00	0.00	0.00	0.00	0.91	0.93	0.97	0.97
Panel D. Bootstrap Analysis for funds that have redemption notice period equal or longer than 60 days										
All Funds	1394	t-Stat	-3.70	-2.95	-2.65	-2.23	1.22	1.53	1.72	2.10
		p-Value	0.00	0.00	0.00	0.00	0.99	1.00	1.00	1.00
Hedge Funds	751	t-Stat	-3.79	-2.91	-2.57	-2.18	1.27	1.57	1.73	2.10
		p-Value	0.00	0.00	0.00	0.00	0.80	0.95	0.99	1.00
Fund of Funds	643	t-Stat	-3.57	-3.09	-2.74	-2.28	1.19	1.52	1.64	2.00
		p-Value	0.00	0.00	0.00	0.00	0.98	0.98	1.00	1.00
Panel E. Bootstrap Analysis for funds with AUM < \$50 millioin										
All Funds	2986	t-Stat	-3.29	-2.67	-2.27	-1.69	1.41	1.74	1.99	2.56
		p-Value	0.00	0.00	0.00	0.00	0.01	0.28	0.38	0.43
Hedge Funds	1691	t-Stat	-3.39	-2.71	-2.34	-1.70	1.46	1.84	2.06	2.59
		p-Value	0.00	0.00	0.00	0.00	0.01	0.05	0.24	0.57
Fund of Funds	1295	t-Stat	-3.19	-2.60	-2.22	-1.65	1.32	1.60	1.81	2.47
		p-Value	0.00	0.00	0.00	0.00	0.34	0.84	0.91	0.53
Panel F. Bootstrap Analysis for funds with AUM < \$150 millioin										
All Funds	4689	t-Stat	-3.39	-2.73	-2.36	-1.81	1.39	1.73	1.97	2.47

		p-Value	0.00	0.00	0.00	0.00	0.01	0.27	0.55	0.78
Hedge Funds	2676	t-Stat	-3.48	-2.80	-2.40	-1.83	1.42	1.79	2.01	2.58
		p-Value	0.00	0.00	0.00	0.00	0.01	0.10	0.32	0.42
Fund of Funds	2013	t-Stat	-3.29	-2.64	-2.29	-1.75	1.34	1.64	1.87	2.28
		p-Value	0.00	0.00	0.00	0.00	0.21	0.81	0.87	0.97

Table 9. Economic Value of Tail Risk Timing – Subsample Analysis

This table reports the results of monthly average risk-adjusted returns of 10 equal-weighted portfolios of hedge funds constructed based on the funds' tail risk timing skill for six kinds of subsamples examined in Section 5-1: funds that do not use leverage (denoted as sample (1)), that use leverage (denoted as sample (2)), that have redemption frequency equal or greater than a quarter (denoted as sample (3)), that have redemption notice period equal or longer than 60 days (denoted as sample (4)), that have asset under management (AUM) below \$50 million (denoted as sample (5)), and that have AUM below \$150 million (denoted as sample (6)). In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate tail risk timing coefficient and construct equal-weighted decile portfolios within a given subsample that are rebalanced each month according to the estimated coefficients. To conserve the space, we only report the results based on portfolios are then held for 12-month periods. For each portfolio and top-minus-bottom timer spread, we report the our benchmark nine-factor alphas (in percent), including Fung-Hsieh (2004) seven factors and Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. Alpha is defined as returns net of what attributable to factor exposures. That is, the alpha is estimated by regression of decile portfolio returns on the above nine factors. The t-statistics based on Newey-West (1987) standard errors with three lags are in the parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	12-month Holding Alpha					
	Sample (1)	Sample (2)	Sample (3)	Sample (4)	Sample (5)	Sample (6)
Portfolio1 (Top Timer)	0.47	0.63	0.48	0.54	0.48	0.51
	(3.20)	(3.77)	(3.57)	(3.65)	(2.87)	(3.32)
Portfolio2	0.45	0.46	0.29	0.31	0.45	0.43
	(2.16)	(3.79)	(2.99)	(2.97)	(2.39)	(3.02)
Portfolio3	0.31	0.33	0.23	0.27	0.43	0.36
	(2.79)	(3.10)	(2.79)	(3.07)	(1.56)	(2.01)
Portfolio4	0.25	0.27	0.23	0.28	0.19	0.20
	(2.66)	(2.79)	(2.75)	(3.40)	(1.80)	(2.07)
Portfolio5	0.18	0.20	0.22	0.27	0.13	0.16
	(1.91)	(2.06)	(2.90)	(3.53)	(1.24)	(1.61)
Portfolio6	0.17	0.22	0.22	0.26	0.13	0.13
	(1.60)	(2.10)	(2.65)	(3.02)	(1.14)	(1.26)
Portfolio7	0.11	0.19	0.21	0.25	0.05	0.09
	(0.92)	(1.66)	(2.31)	(2.55)	(0.45)	(0.72)
Portfolio8	0.08	0.16	0.18	0.21	0.03	0.06
	(0.59)	(1.22)	(1.69)	(1.92)	(0.19)	(0.48)
Portfolio9	0.08	0.16	0.18	0.22	0.02	0.05
	(0.52)	(1.17)	(1.40)	(1.69)	(0.13)	(0.37)
Portfolio10 (Bottom Timer)	0.01	-0.02	0.14	0.11	-0.15	-0.08
	(0.05)	(-0.10)	(0.80)	(0.41)	(-0.64)	(-0.37)
Portfolio1 - Portfolio10	**0.45****	**0.65*****	**0.34*****	**0.44****	**0.63*****	**0.59*****
	(2.47)	**(4.04)**	**(2.73)**	**(1.99)**	**(3.08)**	**(3.49)**

Table 10. Pre-Crisis Period Analysis of Tail Risk Timing

This table presents results of subperiod analysis for our main findings. For the period January 1996 - December 2007, we repeat the bootstrap and univariate portfolio sorting analysis and the results are reported in Panels A and B, respectively. For funds with at least 24 monthly observations, we first estimate following tail risk timing model

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \boldsymbol{\gamma_p} MKT_{t+1}\Delta(Op - Tail)_{t+1} + \sum_{j=1}^{J}\beta_j f_{j,t+1} + \varepsilon_{p,t+1}$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1. MKT_{t+1} is the excess return on the market portfolio in month t+1. $\Delta(\mathrm{Op} - Tail)_{t+1}$ is the monthly change of option-implied tail risk measure in month t+1 described in Section 2-2. $f_{j,t+1}$ includes Fung-Hsieh (2004) seven factors, Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. In this specification, the coefficient γ_p captures tail risk timing ability of hedge fund managers. Panel A reports the cross-sectional distribution of t-statistics of the tail risk timing coefficient and corresponding empirical p-values from bootstrap simulations and Panel B presents monthly returns and 9-factor alphas of 10 equal-weighted portfolios and top-minus-bottom spread of hedge funds constructed based on the funds' tail risk timing skill across various holding periods. The t-statistics based on Newey-West (1987) standard errors with three lags are in the parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% level is indicated by $***$, $**$, and $*$, respectively. The sample period is from January 1996 to December 2007.

Panel A. Bootstrap Analysis for the Pre-crisis Period (1996-2007)

			Bottom t-Statistics for Timing skill				Top t-Statistics for Timing skill			
Strategy Category	# of Funds		1%	3%	5%	10%	10%	5%	3%	1%
All Funds	4699	t-Stat	-3.36	-2.50	-2.12	-1.57	1.20	1.60	1.87	2.52
		p-Value	0.00	0.00	0.00	0.00	0.45	0.10	0.05	0.00
Hedge Funds	2683	t-Stat	-3.48	-2.57	-2.17	-1.64	1.16	1.63	1.89	2.55
		p-Value	0.00	0.00	0.00	0.00	0.97	0.14	0.14	0.01
Fund of Funds	2016	t-Stat	-3.13	-2.37	-2.07	-1.46	1.25	1.58	1.83	2.44
		p-Value	0.00	0.00	0.00	0.00	0.01	0.12	0.13	0.02
Convertible Arbitrage	130	t-Stat	-2.83	-2.75	-1.97	-1.76	0.90	1.63	1.73	1.95
		p-Value	0.02	0.11	0.00	0.00	1.00	0.54	0.82	0.87
Emerging Markets	270	t-Stat	-3.00	-2.27	-2.04	-1.35	1.41	1.83	2.05	3.28
		p-Value	0.03	0.04	0.00	0.03	0.17	0.14	0.19	0.01
Equity Market Neutral	187	t-Stat	-3.09	-1.97	-1.55	-1.15	1.06	1.50	1.81	2.60
		p-Value	0.07	0.98	0.72	0.86	0.83	0.57	0.45	0.21
Event Driven	357	t-Stat	-4.11	-3.36	-2.96	-2.43	0.85	1.26	1.67	1.87
		p-Value	0.00	0.00	0.00	0.00	1.00	1.00	0.91	0.99
Global Macro	166	t-Stat	-4.08	-3.88	-1.92	-1.71	1.40	1.76	2.42	2.69
		p-Value	0.01	0.46	0.03	0.00	0.17	0.25	0.04	0.27
Long/Short Equity Hedge	1227	t-Stat	-3.14	-2.35	-2.06	-1.58	1.25	1.67	1.95	2.56
		p-Value	0.00	0.02	0.00	0.00	0.12	0.04	0.03	0.01
Multi-Strategy	346	t-Stat	-2.44	-1.86	-1.59	-1.29	1.11	1.33	1.58	2.40
		p-Value	0.19	0.93	0.33	0.15	0.81	0.98	0.94	0.26

Table 10 – continued

Panel B. Portfolio Analysis for the Pre-crisis Period (1996-2007)								
	Excess Returns				9-factor Alphas			
	K = 3	6	9	12	K = 3	6	9	12
Portfolio1 (Top Timer)	0.90	0.87	0.76	0.63	0.79	0.75	0.69	0.66
	(3.17)	(3.14)	(2.56)	(1.92)	(5.17)	(5.13)	(4.40)	(4.53)
Portfolio2	0.60	0.63	0.53	0.87	0.50	0.52	0.45	0.76
	(2.77)	(2.98)	(2.34)	(1.95)	(4.44)	(4.77)	(3.84)	(2.45)
Portfolio3	0.51	0.52	0.44	0.32	0.43	0.43	0.39	0.36
	(2.85)	(2.93)	(2.32)	(1.34)	(4.24)	(4.34)	(3.73)	(3.46)
Portfolio4	0.43	0.46	0.39	0.26	0.35	0.38	0.35	0.33
	(2.77)	(3.07)	(2.27)	(1.15)	(4.31)	(4.93)	(4.01)	(3.59)
Portfolio5	0.43	0.45	0.33	0.22	0.35	0.38	0.30	0.29
	(2.85)	(3.13)	(1.95)	(0.98)	(4.19)	(4.72)	(3.23)	(3.18)
Portfolio6	0.48	0.46	0.32	0.22	0.41	0.39	0.31	0.31
	(3.51)	(3.49)	(1.90)	(1.01)	(5.25)	(5.37)	(3.21)	(3.31)
Portfolio7	0.48	0.47	0.33	0.24	0.40	0.40	0.30	0.32
	(3.45)	(3.41)	(1.82)	(1.06)	(4.55)	(4.47)	(2.71)	(3.01)
Portfolio8	0.52	0.50	0.33	0.26	0.41	0.39	0.28	0.32
	(2.91)	(2.83)	(1.57)	(1.05)	(3.83)	(3.63)	(2.12)	(2.60)
Portfolio9	0.57	0.56	0.38	0.31	0.43	0.43	0.30	0.34
	(2.60)	(2.59)	(1.55)	(1.10)	(3.56)	(3.50)	(2.12)	(2.48)
Portfolio10 (Bottom Timer)	0.54	0.50	0.31	0.21	0.29	0.28	0.15	0.19
	(1.36)	(1.33)	(0.79)	(0.51)	(1.20)	(1.22)	(0.64)	(0.80)
Portfolio1 - Portfolio10	**0.36***	**0.37****	**0.45****	**0.42****	**0.50*****	**0.47*****	**0.54*****	**0.47*****
	(1.86)	**(2.02)**	**(2.52)**	**(2.42)**	**(2.84)**	**(2.75)**	**(3.12)**	**(2.79)**

Table 11. Tail-Risk Timing Analysis Controlling for Other Timing Skills

This table reports robustness checks for our main findings. In this table, we repeat the bootstrap and univariate portfolio sorting analysis after controlling for other timing skills such as market, volatility, and liquidity timing skills. For funds with at least 24 monthly observations, we estimate following tail risk timing model with controls for market, volatility, and liquidity timing.

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1}\Delta(Op - Tail)_{m,t+1} + \lambda_p MKT_{t+1}^2 + \delta_p MKT_{t+1}\left(Vol_{t+1} - \overline{Vol}\right) + \theta_p MKT_{t+1}\left(Liq_{t+1} - \overline{Liq}\right) + \sum_{j=1}^{J}\beta_j f_{j,t+1} + \varepsilon_{p,t+1}$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1. MKT_{t+1} is the excess return on the market portfolio in month t+1. $\Delta(Op - Tail)_{m,t+1}$ is the monthly change of option-implied tail risk measure in month t+1 described in Section 2-2. Vol_{t+1} is the market volatility in month t+1 as measured by the CBOE S&P 500 index option implied volatility (i.e., the VIX) and $\overline{Vol}$ is the time series mean of market volatility. Liq_{t+1} is Pastor-Stambaugh (2003) market-liquidity measure and $\overline{Liq}$ is the time series mean of market liquidity. $f_{j,t+1}$ includes Fung-Hsieh (2004) seven factors, Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. In this specification, the coefficient γ_p captures tail risk timing ability of hedge fund managers. In this specification, the coefficients γ, $\boldsymbol{\lambda}$, $\boldsymbol{\delta}$, and $\boldsymbol{\theta}$ measure tail risk timing, market timing, volatility-timing, and liquidity-timing, respectively. Panel A reports the cross-sectional distribution of t-statistics of the tail risk timing coefficient and corresponding empirical p-values from bootstrap simulations and Panel B presents monthly returns and 9-factor alphas of 10 equal-weighted portfolios and top-minus-bottom spread of hedge funds constructed based on the funds' tail risk timing skill across various holding periods. The t-statistics based on Newey-West (1987) standard errors with three lags are in the parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

Panel A. Bootstrap Analysis Controlling for Other Timing Skills

			Bottom t-Statistics for Timing skill				Top t-Statistics for Timing skill			
Strategy Category	# of Funds		1%	3%	5%	10%	10%	5%	3%	1%
All Funds	6147	t-Stat	-3.29	-2.54	-2.18	-1.65	1.40	1.80	2.06	2.50
		p-Value	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.30
Hedge Funds	3567	t-Stat	-3.39	-2.58	-2.24	-1.73	1.45	1.94	2.12	2.56
		p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06
Fund of Funds	2580	t-Stat	-3.27	-2.49	-2.06	-1.54	1.36	1.61	1.84	2.35
		p-Value	0.00	0.97	0.00	0.07	0.00	0.92	0.99	0.97
Convertible Arbitrage	138	t-Stat	-3.76	-3.66	-3.18	-2.06	0.69	1.12	1.45	2.03
		p-Value	0.00	0.00	0.00	0.00	1.00	1.00	1.00	0.94
Emerging Markets	373	t-Stat	-2.40	-1.90	-1.81	-1.30	1.33	1.78	2.12	2.84
		p-Value	0.96	1.00	0.86	0.99	0.15	0.13	0.08	0.08
Equity Market Neutral	234	t-Stat	-3.22	-2.44	-2.10	-1.68	1.32	1.61	1.85	2.79
		p-Value	0.02	0.32	0.03	0.00	0.34	0.71	0.62	0.12
Event Driven	393	t-Stat	-4.21	-3.68	-3.19	-2.75	1.22	1.50	1.67	2.48
		p-Value	0.00	0.00	0.00	0.00	0.97	1.00	1.00	0.81
Global Macro	217	t-Stat	-3.50	-3.06	-2.23	-1.50	1.19	1.78	2.02	2.23
		p-Value	0.00	0.08	0.00	0.09	0.68	0.20	0.23	0.62
Long/Short Equity Hedge	1498	t-Stat	-2.96	-2.43	-2.22	-1.71	1.24	1.65	1.95	2.53
		p-Value	0.00	0.02	0.00	0.00	0.31	0.23	0.09	0.08
Multi-Strategy	714	t-Stat	-2.81	-1.99	-1.56	-1.05	2.02	2.21	2.34	2.99
		p-Value	0.05	1.00	1.00	1.00	0.00	0.00	0.00	0.00

Table 11 – continued

Panel B. Portfolio Analysis Controlling for Other Timing Skills								
	Excess Returns				9-factor Alphas			
	K = 3	6	9	12	K = 3	6	9	12
Portfolio1 (Top Timer)	0.71	0.72	0.75	0.72	0.53	0.54	0.55	0.52
	(2.20)	(2.30)	(2.47)	(2.39)	(3.07)	(3.28)	(3.43)	(3.41)
Portfolio2	0.59	0.70	0.68	0.63	0.41	0.48	0.47	0.43
	(2.41)	(2.73)	(2.82)	(2.77)	(2.82)	(2.73)	(2.95)	(3.10)
Portfolio3	0.58	0.52	0.49	0.45	0.37	0.34	0.33	0.29
	(2.44)	(2.46)	(2.44)	(2.23)	(2.23)	(2.72)	(2.99)	(2.75)
Portfolio4	0.40	0.38	0.37	0.36	0.27	0.26	0.26	0.25
	(1.99)	(1.99)	(1.99)	(1.91)	(2.70)	(2.77)	(2.77)	(2.63)
Portfolio5	0.35	0.35	0.35	0.35	0.24	0.24	0.24	0.24
	(1.89)	(1.91)	(1.93)	(1.90)	(2.47)	(2.50)	(2.52)	(2.52)
Portfolio6	0.28	0.27	0.31	0.37	0.17	0.16	0.18	0.22
	(1.54)	(1.52)	(1.75)	(2.07)	(1.66)	(1.62)	(1.73)	(1.80)
Portfolio7	0.29	0.28	0.26	0.26	0.18	0.16	0.14	0.14
	(1.58)	(1.44)	(1.33)	(1.36)	(1.60)	(1.37)	(1.17)	(1.24)
Portfolio8	0.31	0.27	0.26	0.27	0.17	0.14	0.12	0.13
	(1.58)	(1.35)	(1.26)	(1.31)	(1.42)	(1.08)	(0.97)	(1.04)
Portfolio9	0.32	0.29	0.29	0.31	0.16	0.14	0.14	0.15
	(1.44)	(1.30)	(1.27)	(1.35)	(1.18)	(1.00)	(1.01)	(1.16)
Portfolio10 (Bottom Timer)	0.30	0.27	0.26	0.27	0.04	0.03	0.02	0.03
	(0.91)	(0.85)	(0.81)	(0.83)	(0.21)	(0.17)	(0.12)	(0.16)
Portfolio1 - Portfolio10	**0.41****	**0.45*****	**0.49*****	**0.44*****	**0.49****	**0.51*****	**0.53*****	**0.49*****
	(2.25)	**(2.64)**	**(2.99)**	**(2.93)**	**(2.48)**	**(2.88)**	**(3.15)**	**(3.09)**

Table 12. Tail-Risk Timing Analysis Controlling for Other Timing Skills: Two-way Portfolio Analysis

This table reports robustness checks for our main findings using two-dimensional portfolio analysis. First, for funds with at least 24 monthly observations, we estimate following timing model with controls for hedge fund risk factors.

$$r_{p,t+1} = \alpha_p + \beta_p MKT_{t+1} + \gamma_p MKT_{t+1} X_{m,t+1} + \sum_{j=1}^{J} \beta_j f_{j,t+1} + \varepsilon_{p,t+1}$$

where $r_{p,t+1}$ is the excess return for fund p in month t+1. MKT_{t+1} is the excess return on the market portfolio in month t+1. $X_{m,t+1}$ is one of the following four kinds of market characteristics; the monthly change of option-implied tail risk measure ($\Delta(Op-Tail)_{m,t+1}$) in month t+1 described in Section 2-2, the square of market returns (MKT^2_{t+1}) capturing market timing ability, the demeaned market volatility in month t+1 as measured by the CBOE S&P 500 index option implied volatility (i.e., the VIX), and Pastor-Stambaugh (2003) market-liquidity measure demeaned by the time series mean of market liquidity. $f_{j,t+1}$ includes Fung-Hsieh (2004) seven factors, Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. Then, at the beginning of every month, we independently sort all funds into quintile portfolios based on option-implied tail risk timing coefficients and tercile portfolios based on market timing, market volatility timing, or liquidity timing coefficients; 5 by 3 portfolios. Portfolios are then held for different holding periods, i.e. 3-, 6-, 9-, and 12-month. For each 15 portfolio and top-minus-bottom timer spread (Portfolio1 – Portfolio5), we calculate nine-factor alphas (in percent) consistent to former analysis. Columns named as 'Low', 'Middle', and 'High' indicate the bottom, middle, and top portfolios based on market, liquidity, or volatility timing coefficients, and 'Portfolio1 (Portfolio 5)' is top timer (bottom timer) portfolio consisting of funds with lower (higher) timing coefficients to option-implied market tail risk. To conserve the space, we omit the results of Portfolio 2 and 4. The t-statistics based on Newey-West (1987) standard errors with three lags are in the parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Market Timing Coefficient			Liquidity Timing Coefficient			Volatility Timing Coefficient		
	Low	Middle	High	Low	Middle	High	Low	Middle	High
Panel A. 3-month Holding									
Portfolio1 (Top Timer)	0.50	0.38	0.66	0.44	0.31	0.55	0.54	0.41	0.44
	(2.98)	(2.78)	(3.62)	(3.00)	(2.75)	(2.70)	(3.26)	(2.99)	(2.43)
Portfolio3	0.09	0.16	0.38	0.15	0.19	0.26	0.28	0.16	0.21
	(0.74)	(1.67)	(3.38)	(1.16)	(2.13)	(2.21)	(2.44)	(1.77)	(1.89)
Portfolio5 (Bottom Timer)	0.08	0.15	0.14	0.26	0.12	0.22	0.18	0.10	0.18
	(0.36)	(1.03)	(0.60)	(1.33)	(0.74)	(1.58)	(1.07)	(0.82)	(0.91)
Portfolio1 - Portfolio5	**0.43****	**0.23***	**0.52****	**0.18**	**0.19***	**0.33****	**0.37****	**0.31****	**0.26**
	(2.25)	**(1.75)**	**(2.49)**	**(1.17)**	**(1.72)**	**(2.36)**	**(2.48)**	**(2.54)**	**(1.39)**
Panel B. 6-month Holding									
Portfolio1 (Top Timer)	0.51	0.51	0.56	0.47	0.37	0.49	0.54	0.45	0.48
	(3.29)	(3.60)	(3.49)	(3.38)	(3.46)	(2.58)	(3.38)	(3.44)	(2.83)
Portfolio3	0.16	0.17	0.29	0.20	0.17	0.22	0.26	0.17	0.22
	(1.43)	(1.86)	(2.56)	(1.67)	(1.96)	(1.98)	(2.31)	(1.87)	(1.99)
Portfolio5 (Bottom Timer)	0.06	0.09	0.13	0.26	0.11	0.19	0.16	0.04	0.13
	(0.32)	(0.62)	(0.60)	(1.36)	(0.76)	(1.31)	(0.93)	(0.34)	(0.72)
Portfolio1 - Portfolio5	**0.45*****	**0.42*****	**0.43****	**0.21**	**0.26****	**0.30****	**0.37*****	**0.40*****	**0.35****
	(3.01)	**(3.00)**	**(2.32)**	**(1.47)**	**(2.54)**	**(2.38)**	**(2.74)**	**(3.25)**	**(2.23)**
Panel C. 9-month Holding									
Portfolio1 (Top Timer)	0.54	0.52	0.50	0.48	0.38	0.52	0.53	0.48	0.49
	(3.70)	(3.63)	(3.23)	(3.67)	(3.59)	(2.88)	(3.33)	(3.81)	(3.19)
Portfolio3	0.22	0.17	0.21	0.20	0.16	0.21	0.24	0.16	0.21
	(1.99)	(1.89)	(1.81)	(1.72)	(1.83)	(1.94)	(2.21)	(1.78)	(1.95)
Portfolio5 (Bottom Timer)	0.10	0.07	0.09	0.21	0.09	0.16	0.12	0.06	0.08
	(0.55)	(0.45)	(0.43)	(1.13)	(0.65)	(1.06)	(0.69)	(0.42)	(0.46)
Portfolio1 - Portfolio5	**0.44*****	**0.46*****	**0.41****	**0.28****	**0.29*****	**0.36*****	**0.41*****	**0.42*****	**0.41*****
	(3.34)	**(3.24)**	**(2.40)**	**(2.09)**	**(2.95)**	**(3.19)**	**(2.91)**	**(3.42)**	**(2.82)**
Panel D. 12-month Holding									
Portfolio1 (Top Timer)	0.54	0.49	0.48	0.48	0.38	0.50	0.52	0.47	0.49
	(3.96)	(3.69)	(3.24)	(3.80)	(3.56)	(2.96)	(3.32)	(3.91)	(3.47)
Portfolio3	0.24	0.17	0.16	0.18	0.16	0.21	0.24	0.15	0.20
	(2.29)	(1.96)	(1.35)	(1.53)	(1.86)	(1.92)	(2.15)	(1.77)	(1.90)
Portfolio5 (Bottom Timer)	0.12	0.07	0.07	0.18	0.11	0.15	0.14	0.07	0.07
	(0.69)	(0.45)	(0.32)	(0.97)	(0.76)	(1.06)	(0.77)	(0.53)	(0.43)
Portfolio1 - Portfolio5	**0.42*****	**0.42*****	**0.41*****	**0.31****	**0.27*****	**0.35*****	**0.38*****	**0.40*****	**0.42*****
	(3.73)	**(3.33)**	**(2.56)**	**(2.47)**	**(2.83)**	**(3.53)**	**(2.79)**	**(3.66)**	**(3.27)**

Table 13. Controlling for Other Managerial Skills

This table repeats the Fama-Macbeth (1973) cross-sectional regressions in the presence of other managerial skill measures documented in prior studies. That is, we report the Fama-MacBeth regression results for hedge fund performance, both excess return and alpha, on funds' tail risk timing, while controlling for other skill measures and fund characteristics. In each month, for each fund with at least 18 monthly observations in the past 24 months, tail risk timing skill is estimated by regressing the fund's excess returns on the market index and its interaction with tail risk measure, with controls of the Fung-Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor-Stambaugh (2003) liquidity factor. Alternative skill measures considered include hedging skill proxy (R-Square) suggested by Titman and Tiu (2011) and down-side returns (Downside-Returns) discussed by Sun, Wang, and Zheng (2014). Details on the construction and description of those two measures are summarized in Section 5-4. Control variables are the same as in Table 7. For brevity, we only report the estimation results for the coefficient of interest, Timing Beta and alternative measures for managerial skills. The estimation results for Fama-Macbeth regression in the presence of hedge skill, down-side returns, and both proxies simultaneously are displayed in Panels A and B. The t-statistics are based on Newey-West (1987) standard errors with three lags. Significance at the 1%, 5%, and 10% level is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Dependent Variable							
	Excess Returns				9-Factor Alphas			
Variable	K = 3	6	9	12	K = 3	6	9	12
Panel A. Regression Results without Characteristics Control								
Intercept	0.0025	0.0029	0.0034	0.0039	0.0040	0.0043	0.0047	0.0051
	(1.45)	(2.03)	(2.90)	(3.73)	(3.26)	(4.13)	(5.21)	(6.13)
Timing Beta	**-0.0033*** **	**-0.0038*** **	**-0.0040*** **	**-0.0039*** **	**-0.0036*** **	**-0.0039*** **	**-0.0039*** **	**-0.0035*** **
	(-2.81)	**(-3.76)**	**(-4.84)**	**(-5.64)**	**(-3.57)**	**(-4.26)**	**(-5.00)**	**(-5.45)**
R-Square	0.0011	0.0000	-0.0009	-0.0012	-0.0017	-0.0022**	-0.0030***	-0.0035***
	(0.57)	(-0.00)	(-0.70)	(-1.01)	(-1.39)	(-2.10)	(-3.18)	(-3.80)
Downside-Returns	0.0905	0.0766	0.0563	0.0395	0.1099***	0.1031***	0.0885***	0.0757***
	(1.53)	(1.50)	(1.29)	(1.10)	(3.35)	(3.75)	(3.94)	(3.76)
Characteristics Control	No	No	No	No	No	No	No	No
Strategy Dummy	No	No	No	No	No	No	No	No
Adj-R^2	0.121	0.123	0.122	0.116	0.061	0.069	0.069	0.066
# of Obs	388,975	370,571	352,189	333,824	388,975	370,571	352,189	333,824
Panel B. Regression Results with Characteristics Control								
Intercept	0.0136	0.0149	0.0142	0.0136	0.0145	0.0162	0.0154	0.0146
	(3.36)	(3.57)	(3.96)	(4.22)	(3.45)	(3.82)	(4.05)	(4.25)
Timing Beta	**-0.0022** **	**-0.0027*** **	**-0.0024*** **	**-0.0022*** **	**-0.0021** **	**-0.0025*** **	**-0.0023*** **	**-0.0021*** **
	(-2.21)	**(-2.78)**	**(-3.53)**	**(-3.84)**	**(-2.50)**	**(-3.26)**	**(-3.71)**	**(-3.77)**
R-Square	0.0005	-0.0006	-0.0014	-0.0017	-0.0021	-0.0023**	-0.0029***	-0.0032***
	(0.25)	(-0.41)	(-1.09)	(-1.46)	(-1.54)	(-1.98)	(-2.96)	(-3.91)
Downside-Returns	0.0535	0.0353	0.0148	0.0006	0.0768**	0.0682**	0.0559**	0.0451**
	(0.84)	(0.66)	(0.33)	(0.02)	(2.31)	(2.42)	(2.35)	(2.15)
Characteristics Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strategy Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj-R^2	0.187	0.192	0.198	0.197	0.109	0.123	0.130	0.132
# of Obs	272,649	258,523	244,067	229,574	272,649	258,523	244,067	229,574

Figure 1. Option-Implied Tail Risk Measure and 1-Month Subsequent Realized Market Tail Measure

This figure plots the standardized principal components of option-implied tail risk measures, named as 'Op-Tail' and realized market tail after 1-month. Option-implied tail risk measure (Op-Tail) is constructed as the first principal components of risk-neutral skewness (R.N. Skew), risk-neutral kurtosis (R.N. Kurt), the slope of the implied volatility smirk for out-of-the-money S&P 500 put options (S&P Slope), and the equally weighted average of the slopes of implied volatility smirk for out-of-the-money put options of individual stocks (Indi Slope). Details on the construction and description of those measures are summarized in Section 2-2. The realized market tail is measure as the minimum daily return of CRSP value-weighted market returns including dividend for a corresponding month. To emphasize comparison, the monthly series of the minimum daily return is scaled to have mean zero and variance one. The sample period is from January 1996 to December 2012.

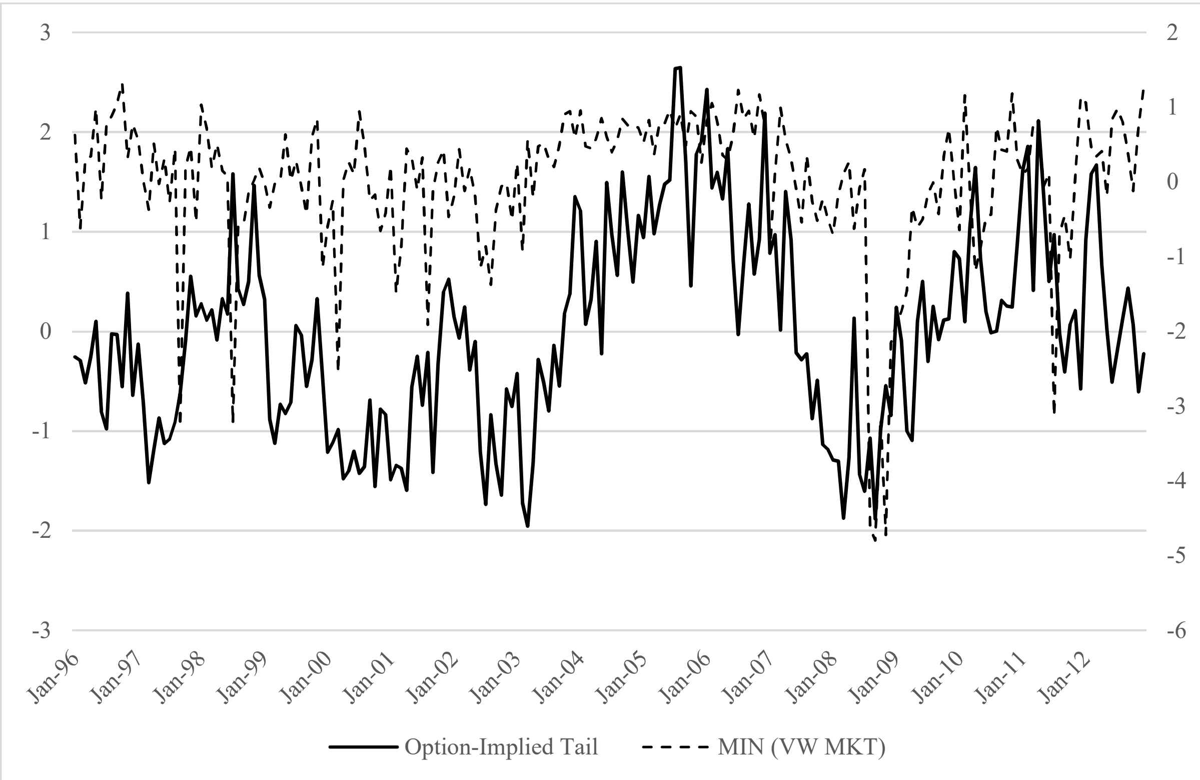
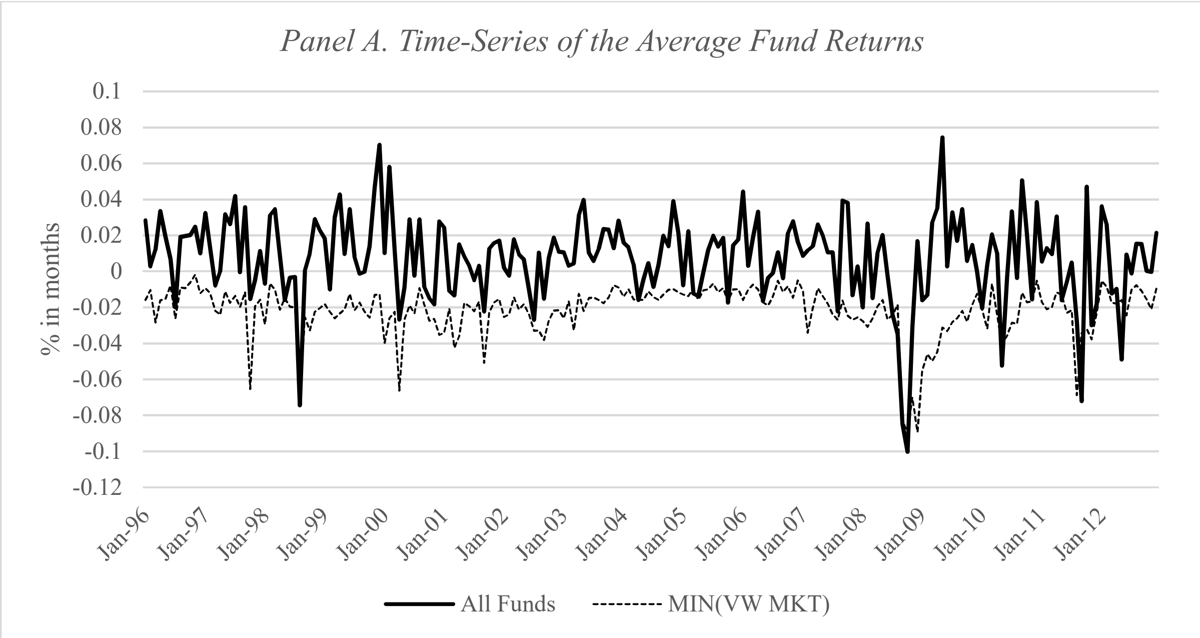


Figure 2. Times-Series Average of the Aggregate Hedge Fund Returns

This figure plots the time-series average of aggregate hedge fund returns and realized market tail returns for our sample periods from January 1996 to December 2012. Realized market tail is measured as the minimum daily returns within a month. Panel A shows the equally weighted average of all hedge fund returns in our sample. Panel B depicts the time-series average of hedge funds returns except for 'Fund of Funds'. The sample period is from January 1996 to December 2012.



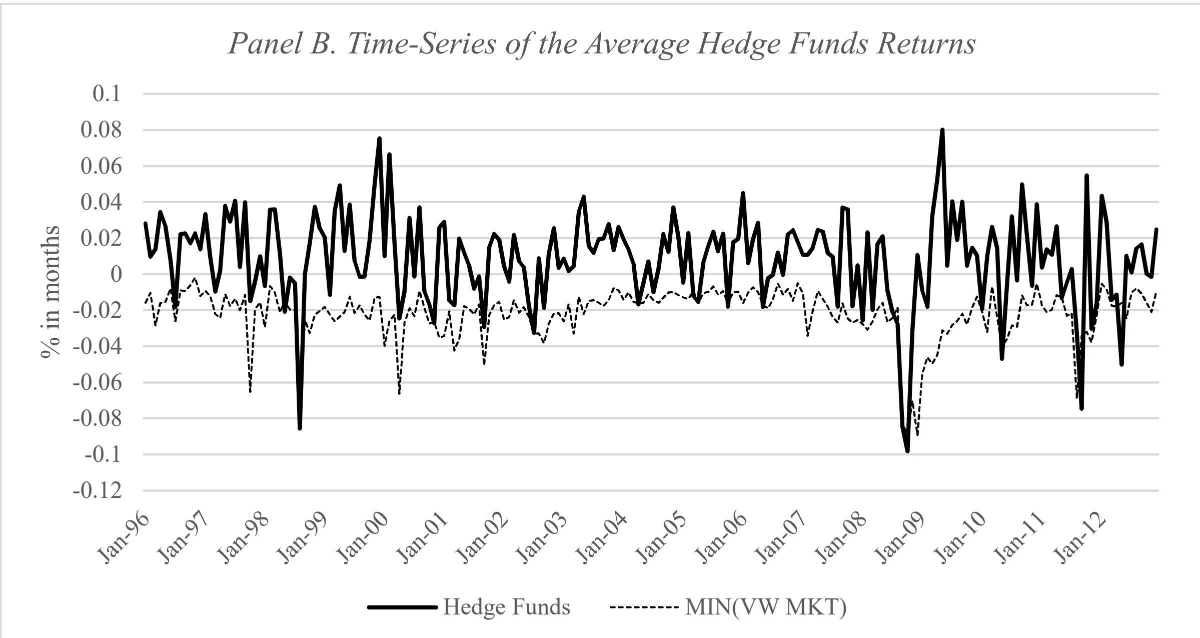


Figure 3. 12-Month Holding-Period Out-of-Sample Alphas for Decile Portfolios

This figure depicts out-of-sample alphas for our sample hedge funds. In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate tail risk timing coefficient and construct equal-weighted decile portfolios that are rebalanced each month based on the estimated coefficients. This figure displays the full distribution of out-of-sample alphas of decile portfolios for 12-month holding period. The gray bars indicate the results for all funds (including hedge funds and funds of funds) and the hatched bars show those for hedge funds only. The sample period is from January 1996 to December 2012.

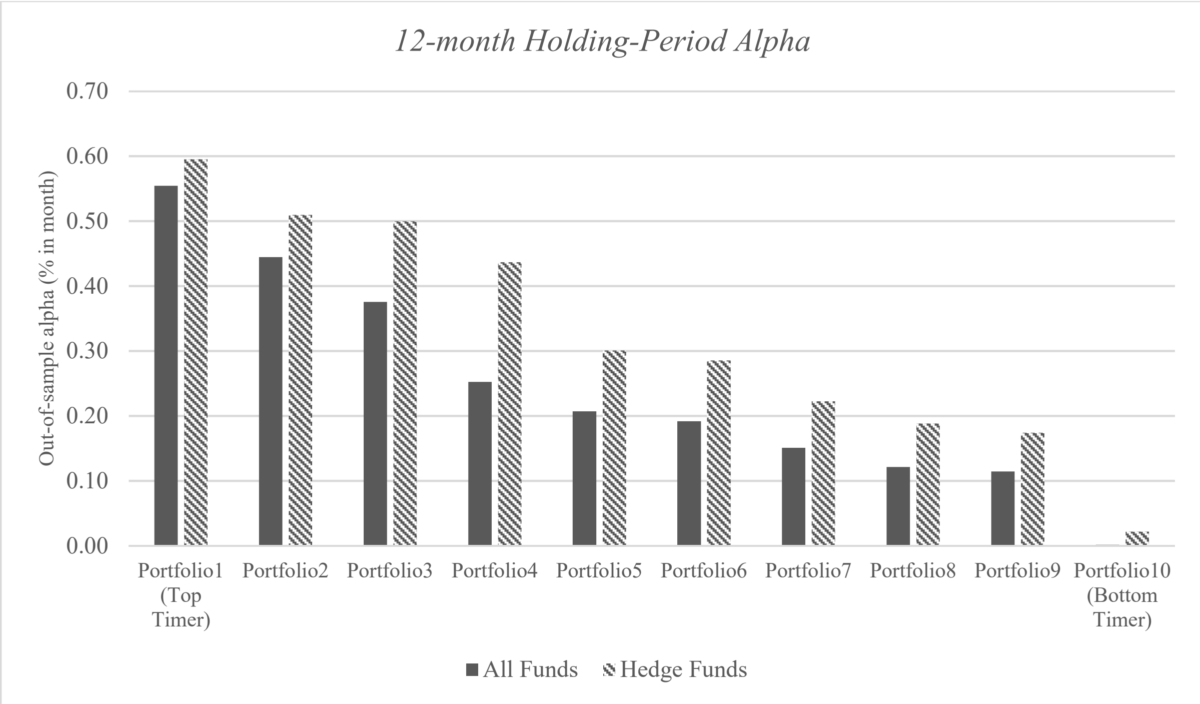


Figure 4. Out-of-Sample Alphas for Top verses Bottom Timer Portfolios

This figure depicts out-of-sample alphas for the portfolios consisting of top verses bottom timing funds for a holding period of three, six, nine, or twelve months. In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate tail risk timing coefficient and construct equal-weighted decile portfolios that are rebalanced each month based on the estimated coefficients. Panel A reports results for all funds (including hedge funds and funds of funds), and Panel B reports results for hedge funds only. The sample period is from January 1996 to December 2012.

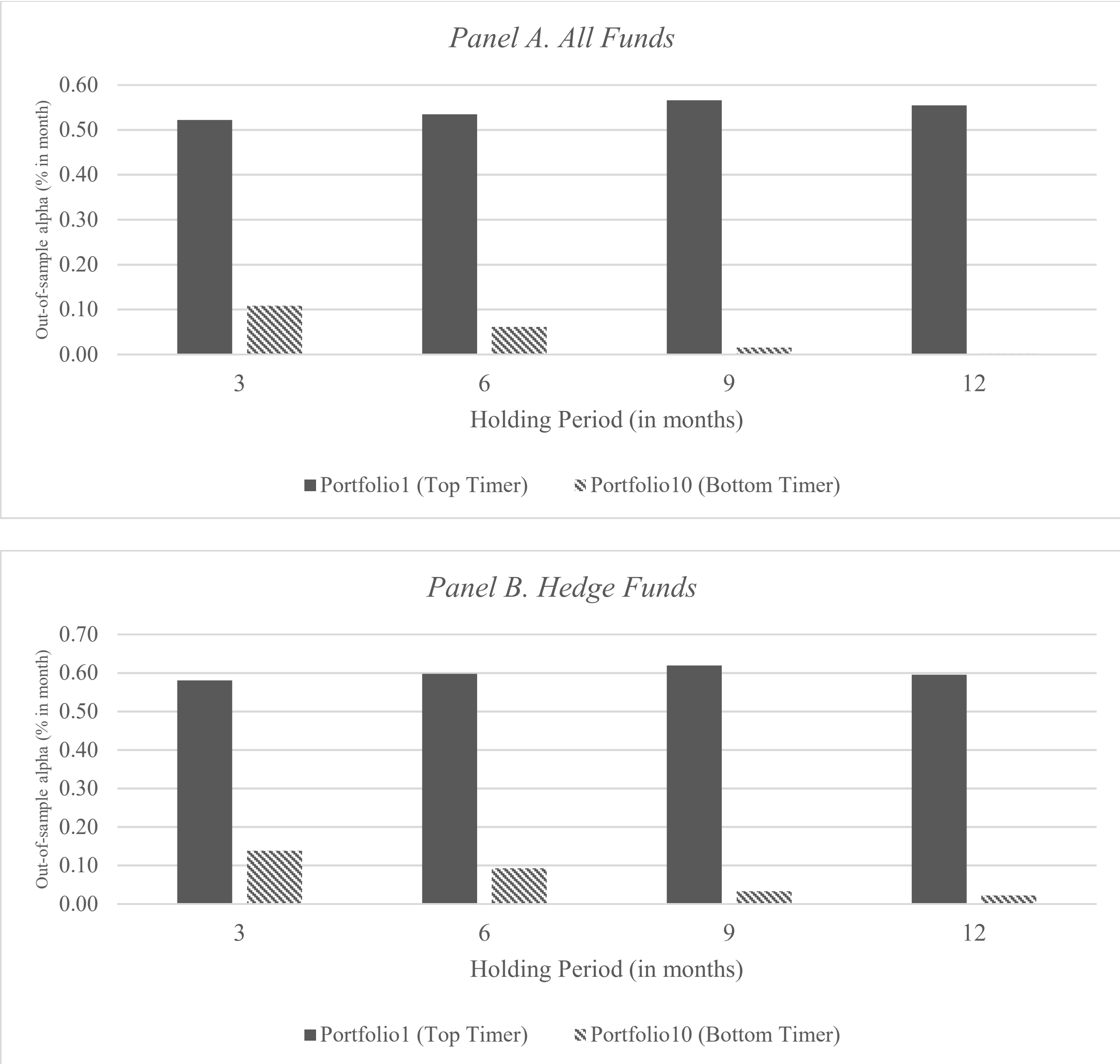


Figure 5. Persistency of Tail Risk Timing

This figure displays an out-of-sample tail risk timing ability of decile portfolios for a 12-month holding period. In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate tail risk timing coefficient and assign all funds into ten portfolios that are rebalanced each month based on the estimated coefficients. We then estimate the timing model Eq. (13) for each hedge funds composing decile portfolios using 24-month holding periods to evaluate fund managers' subsequent timing skill and display an average of the estimates across decile portfolio. The sample period is from January 1996 to December 2012.