Do Hedge Funds Time the Market Tail Risk? Evidence from Option-Implied Tail Risk*

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ABSTRACT

This paper focuses on an unexplored dimension of fund managers' timing ability: market-wide tail risk implied by information in options markets. We investigate whether hedge fund managers can strategically time market tail risk through adjusting their portfolios' market exposure to changes in market tail risk. Using an extensive sample of equity-oriented hedge funds, 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 significant economic value to investors. Specifically, top-ranked hedge funds outperform bottom-ranked funds by 5–7% annually after adjusting for risk factors. Our overall results are robust to various fund characteristics, sub-sample and sub-period analysis, other timing abilities, and other hedge funds' managerial skills. Our examination emphasizes the role of market-wide option-implied tail risk in hedge fund managers' skill and performance.

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

JEL classification: G2, G11

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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 thought to pursue strategies that generate steadily positive returns or alphas but that sometimes bring a tremendous loss, causing the hedge fund company itself to fail. Most such hedge fund failures are related to "tail" events in capital markets. For example, Tiger Management closed and Quantum Fund recorded substantial losses in 2000 due to a stock market crash after the IT–tech bubble burst. In this way, "tail" events of capital markets have played a crucial role in the life cycle of the hedge fund industry.

Thus, we pose a question: Can hedge funds managers, considered sophisticated and professional investors, forecast and react strategically to changes in market "tail" risk? After the pioneering Treynor and Mazuy (1966), a great deal of the literature attempts to identify the presence of fund managers' timing ability, and academics have shown a lot of interest in timing ability of professional managers.[2] Nevertheless, the majority of studies focus on the ability to time market returns, and there is a paucity of studies identifying 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 the hedge fund industry, with respect to a critical but unexplored dimension of market conditions—market tail risk. Specifically, we 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 these questions is essential to improving our comprehension of managerial skills in hedge funds and the economic consequences of these

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[1] For instance, Long-Term Capital Management (LTCM) collapsed in 1998 because Russia defaulted on its debt in August 1998; Tiger Management closed after the 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; and 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 Korajczyk, 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, Simonov, 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.

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 mentioned above, market-wide tail risk plays a key role for 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, resulting in direct and tremendous damage to portfolios and investor welfare. Particularly, Kelly and Jiang (2012) argue that an increase in market-wide tail risk is 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 two hedge funds of Bear Stearns in 2007 were accompanied by deep market crashes; such events impose significant adverse effects on the stability of the entire financial system. In this regard, investigating whether hedge fund managers actually possess timing ability with respect to market tail risk is of great importance from an economic perspective. Second, hedge funds have enjoyed explosive growth over the last two decades, and their managers have long been regarded as the most sophisticated and professional investors. Thus, if professional asset managers strategically time markets, it would be natural to ask whether these professional managers have timing ability for market tail risk. Also, a large body of literature suggests evidence for 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, previous studies document 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 the distinct features 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 the hedge fund industry.

To investigate timing ability of hedge fund managers, we utilize the well-established timing framework proposed by Treynor and Mazuy (1966) and apply a market-wide tail risk measure implied by information in options markets. The past studies document that information in options prices not only indicate the contemporaneous state of the underlying asset, but also provides 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 declines in market capitalization are usually accompanied by rare events, sometimes exacerbated by fear, and persist for a few months. In this regard, we judge that information on market crash risk and current market state should be present in options markets. Furthermore, the literature shows that market-wide, high-moment risks implied by index options have 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); these factors are widely used in previous studies and are highly correlated with market tail risk. Then, we make a single index of option-implied tail risk using PCA analysis. Our timing model is similar to the volatility timing model (e.g., Busse, 1999), because past studies use the VIX index as a proxy for market volatility, which is also implied by options. However, to the best of our knowledge, the present study is the first to apply an option-implied tail risk measure to examine hedge fund managers' timing ability.

Using an extensive sample of 6,147 equity-oriented hedge funds over the period 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 the 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 the statistical significance of individual funds' timing ability from pure luck, we conduct a bootstrap analysis used in the literature (e.g., Cao, Chen, Liang, and Lo, 2013). The result suggests that our empirical findings are not attributable to pure luck or multi-sample bias, and there exist professional hedge fund managers exhibiting significant tail risk timing ability.

We then conduct simple univariate portfolio analysis for several holding periods to check whether top-ranked hedge funds generate significant future abnormal returns to examine whether 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 past timing tail risk skills with 12-month holding periods; the results

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[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 the OTM put volatility smirk.

indicate that hedge funds in the greatest tail risk timing portfolio (top timers) outperform those 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. This is because top timers effectively reduce their market exposure when option-implied market tail risk increases, and this circumstance usually occurs when the market-wide uncertainty increases, market exhibits higher volatility, and market often shows downward crashes. In addition, we conduct Fama–MacBeth (1973) cross-sectional regression to confirm that our economic value from tail risk timing skill is robust to other fund characteristics associated with future fund performance. The results indicate that our inference on tail risk timing ability holds after other fund characteristics are controlled for. Next, we examine whether tail risk timing ability persists over time using out-of-sample tests based on portfolio analysis. Our simple analysis finds strong evidence of persistence in 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 a monotonic relation with the past timing coefficient, implying that tail risk timing ability reflects true managerial skill and that such 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 in the hedge fund sample causes biases to our main inferences on tail risk timing ability. In detail, there is the possibility that our results on tail risk timing are driven by use 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 periods such as the 2008–2009 financial crisis period, when extreme market tail events occurred. Thus, to mitigate the biases caused by the infrequent nature of extreme events, we repeat our main analysis using the subsample of pre-crisis periods (January 1996 to December 2007). In summary, we rerun our main estimation approach based on the above concerns and find that our tail risk timing skill measure remains 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 return, volatility, liquidity, and even tail risk seem to be highly correlated with each other. Also, it is well established that hedge fund managers have significant timing skill with respect to such market conditions.[4] In this regard, to alleviate concerns that our findings

[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

could simply be attributable to other types of timing skill, we explicitly control for other dimensions of timing ability in our baseline timing model, including market volatility and liquidity timing skill. Our main results do not qualitatively or quantitatively change even after controlling for other timing aspects in our baseline timing model. Also, the economic value driven by tail risk timing ability remains robust to volatility and liquidity timing abilities, implying that managers' tail risk timing ability does matter for superior fund performance.

Finally, we 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 skill. Thus, we consider two other kinds of managerial skill proxy 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, Wang, and Zheng (2014). Then, we conduct a cross-sectional regression to check the final robustness, to determine whether tail risk timing ability remains significant in the future performance of hedge funds.

We contribute to the literature in several ways. First, our paper extends the timing literature by suggesting a new dimension of hedge fund timing ability, that is, timing for market-wide tail risk implied by options. Undoubtedly, market-wide extreme event risk (or tail risk) critically affects the performance of professional fund managers, especially hedge fund managers. To the best of our knowledge, this paper is the first to investigate timing ability with regard to market tail risk. We find that there are hedge funds able to time the market by successfully adjusting their exposure to the market as market-wide tail risk changes; we show that such funds perform well in the future. Moreover, our paper presents a comprehensive analysis regarding timing ability of hedge funds managers. Given the increasing importance of market tail risk concerns in the entire asset management industry, as noted anecdotally above, 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 confirm that our main inferences are not attributable 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 several managerial skill proxies, suggesting that our main arguments on tail risk timing of hedge funds and its economic value are economically significant.

market when the market goes down rather than 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.

The remainder of this paper proceeds as follows. Section 2 describes the tail risk timing model and our option-implied tail risk measure. Section 3 introduces our hedge fund sample. Sections 3 and 4 present the results of our main empirical findings, along with several additional tests and robustness checks. Finally, Section 5 describes our conclusions.

2. Option-Implied Tail Risk Timing Model

2.1 Tail Risk Timing Model

In this section, we build a 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 fund manager forecasts, resulting in an important source of superior performance. First, we utilize the 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 fund generates 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 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 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 the manager's forecast of 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 on which they concentrate (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 the timer's forecast about market conditions by ignoring higher-order terms (e.g., Shanken, 1990). Following the priors, we 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, that is, how market beta varies with forecasts about market conditions. We evaluate an unexplored dimension of timing skill, namely, tail-risk timing—the ability to strategically adjust portfolio exposures to the market to have a low loading on the market portfolio when market tail risk is expected to be high. Therefore, we specify Eq. (3) as follows:

$$\beta_{p,t} = \beta_p + \gamma_p\left(Tail\ Risk_{m,t+1} + \nu_{t+1}\right), \tag{3}$$

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, ν_{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, that is, $Tail\ Risk_{m,t+1}$, using information extracted from options markets. Details on construction and description of tail risk are summarized in the next section.

Finally, we 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:

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

The tail-risk timing model in Eq. (4) is in line with the existing models of market timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p(MKT_{t+1} + \nu_{t+1})$], volatility timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p\left(Vol_{m,t+1} - \overline{Vol_m} + \nu_{t+1}\right)$], and liquidity timing [i.e., $\beta_{p,t} = \beta_p + \gamma_p\left(L_{m,t+1} - \overline{L_m} + \nu_{t+1}\right)$], 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 market exposure when market tail risk is expected to be high.

In the estimation process, we additionally include several factors widely used in the hedge fund literature. Specifically, we first consider the traditional three factors of Fama and French (1993), that is, market, size, book-to-market. Furthermore, it is well known that hedge funds use dynamic strategies (e.g., Fund and Hsieh, 1997, 2001) and invest in 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 currencies, bonds, and commodities proposed by Fung and Hsieh (2004). Finally, we add the Carhart (1997) momentum factor and 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 stock market exposure is most closely related to 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:

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

where $r_{p,t+1}$ is excess return for fund p in month t+1, and MKT_{t+1} is 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 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 exposure to the 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 defined as the risk of rare and quite large downside events. Statistically, tail events are possible outcomes placed on the left-tail of the 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 another on individual stock data. The option-based approach includes the risk-neutral skewness and kurtosis proposed by Bakshi, Kapadia, and Madan (2003). Also, Bollerslev and Todorov (2011) estimate tail risk using high-frequency data. Finally, Kelly and Jiang (2014) measure time-varying tail risk from the cross-section of stock returns. We select the option-implied measure of market tail risk.

There are several reasons to measure market tail risk based on option market data. First, past studies show that information in option prices provides 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 possessed by rational arbitrageurs and expectations of market participants. We measure the future potential for tail events of stock markets. Thus, options could reflect a true *ex-ante* measure of expectations on the future return distribution of the stock market. Second, the literature shows a significant relationship between market-wide high-moment risks implied by index options and hedge fund returns (Agarwal et al., 2010), and argues that that the negative jump (or tail) risk is sufficiently reflected in 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 the options market. Furthermore, there are data availability issues for high-frequency data, restricting the 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 options database is available from 1996. Hence, it is natural to investigate our research question using a combined sample of hedge funds and options markets. Finally, the tail risk measure proposed by Kelly and Jiang (2014) is implied by the cross-section of individual stock returns. Although these authors assess that the impact of aggregate firm-level measures from individual stocks could yield a market-wide measure, their measure is insufficient to capture all market-wide information regarding tail risk.[5] On the other hand, the option could have its underlying asset be both an individual stock and a 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 proxy for option-implied tail risk is the risk-neutral moments proposed by Bakshi, Kapadia, and Madan (2003). Agarwal, Bakshi, and Huij (2010) investigate the exposures of hedge fund returns to volatility, skewness, and kurtosis risks implied from 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 an 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 of quadratic, cubic, and quartic payoffs. These authors express the τ-maturity of an asset that pays the quadratic, cubic, and quartic return on the base asset as:

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

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

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

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 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]

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

[6] In addition to discrete trapezoidal integrations, we can calculate the integral in Eq. (6), (7), and (8) using a 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 an available moneyness range and extrapolate using the last known value to fill a thousand grid points in

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:

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

Our second proxy for option-implied tail risk is the slope of the implied volatility smirk for OTM put options. The literature argues that the negative jump risk is reflected by the overpricing of deep OTM put options, and investor 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 a volatility smirk by calculating a regression coefficient using options with 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 slope of the volatility smirk: one with S&P 500 Index options and the other with individual stock options. To account for the cross-section of individual stock level risk, we take average of 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, RN Skew) and kurtosis (hereafter, RN Kurt) of S&P 500 Index options using trapezoidal approximation. We use only 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 estimate the moments only for days that have at least two OTM put and call prices available. Second, we compute the slope of OTM put-implied volatility smirk of S&P 500 Index options (hereafter, S&P Slope) using

the given moneyness range. Then, we convert these interpolated volatilities into call and put prices to calculate the integral. We also use this approach to measure option-implied risk-neutral moments, but our main empirical results do not change.

OTM put options with positive open interest, non-zero bids, and 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 an 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 maturity higher than 30, and another set for maturity lower than 30. Then, the estimates are linearly interpolated to arrive at a daily measure with constant 30-day maturity. Finally, since the hedge fund database has monthly frequency, 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 RN Skew and RN Kurt is -0.92. That is, the market is more likely to be leptokurtic or fat-tailed when the market is expected to be left-tailed, suggesting that the fat tail might be caused by downside jumps rather than upside ones. Also, RN Skew has positive correlations with S&P Slope and Indi Slope, with values 0.55 and 0.40, respectively, and RN Kurt has negative correlations with S&P Slope and Indi Slope with values -0.60 and -0.48, respectively. These correlations imply that steeper and more negative slopes of volatility smirks are associated with lower value of RN Skew and higher value of RN Kurt. Considering that the steeper slope means potentially large negative jumps, these correlation values are reasonable. Finally, S&P Slope and Indi Slope are positively correlated.

To construct the 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, we rescale the measure to have unit variance and zero mean. The resulting option-implied tail risk is as follows:

$$\begin{aligned} Op - Tail_{m,t} = {} & -0.553 \cdot R.N.Skew_t + 0.574 \cdot R.N.Kurt_t \\ & -0.461 \cdot S\&P\ SLpoe_t - 0.388 \cdot Indi\ Slope_t \end{aligned} \quad (12)$$

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*) is plotted in Figure 1 as a straight line. Figure 1 also plots the standardized realized market tail after one month as a dotted line, measured as the daily minimum return within a month, and we can check that a sharp increase in *Op-Tail* implied sharp is associated with an increase in market downside returns, for example, in October 1997 (Asia Crisis) and August 1998 (Collapse of LTCM). Thus, in the similar spirit of Cao et al. (2013), which investigating whether hedge funds time a change of market liquidity, we attempt to examine the managerial ability of hedge funds for timing a dramatic change of tail risk implied by the option markets.[7] Therefore, we focus on innovation or change of *Op-Tail*, not the level of *Op-Tail*, and we subtract the lagged value of *Op-Tail* in the previous month and define $\Delta(Op - Tail)$ as the final option-implied tail risk, which we focus on. Our final tail risk timing model Eq. (5) becomes:

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

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 in Eq. (12), and this change value is standardized to have mean zero for ease of interpretation, following the de-meaning process of other timing studies (e.g., Busse, 1999; Cao, Chen, Liang, and Lo, 2013). The other factors are the same as in Eq. (5).

Before we conduct an empirical examination of hedge fund tail risk timing, we check the properties of our option-implied tail risk measure; $\Delta(Op - Tail)$. We conduct simple regression analysis to determine the relationship between the 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 with distribution of market portfolios. Then, we conduct a 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 $Tail$ represents the above four proxies for realized market tail and $\Delta(Op - Tail)$ is the option-implied tail risk measure. Panel B of 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 with contemporaneous market realized tail proxies, such as skewness and minimum return within a month. Also, in terms of skewness and kurtosis, our option-implied measure does not significantly relate to the previous *ex-post* market tail. However, $\Delta(Op - Tail)$ has a significant impact on future market minimum daily return (realized

[7] *Op-Tail* is fairly persistent, with a monthly AR(1) coefficient of 0.77, which is statistically significant.

market tail events or market crash). For example, a one standard deviation increase of change in the option-implied tail is significantly associated with a decrease in market downside return of 0.23 times its standard deviation. On the other hand, $\Delta(Op - Tail)$ does not significantly affect the future market upside return, and the sign is negative. Furthermore, we can conclude that our option-implied tail measure is significantly responsive to the past market *ex-post* left and right tails. When the market maximum returns increase or minimum returns decrease, the option-implied measure is becoming larger. Figure 1 plots the time-series of $Op - Tail$ and 1-month ahead of the time-series of minimum daily value-weighted market portfolio within a month, and we can check that the sharp increase in option-implied tail is correlated to a decrease in market ex-post left-tail in the near future.

3. Hedge Fund Data

3.1 Hedge Fund Sample

We construct our hedge fund sample from the Lipper TASS (hereafter TASS) database, which is one of the most extensive hedge fund data sources and is widely used for empirical examination in the hedge fund literature. The database reports net-of-fee monthly returns, assets under management, and contains information about a variety of fund characteristics, such as lockup, redemption frequency, incentive and management fee rates, inception dates, and investment style.[8] Because the 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 in the hedge fund database.

In 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.[9] To control for backfill bias (or incubation bias),

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

[9] 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.

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 11 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 risk in the stock market, especially as implied by options market, we drop the categories fixed income arbitrage, dedicated short bias, and managed futures so that our sample consists only of equity-oriented funds. Because funds of funds are treated as a separate category, some important analysis is conducted only on the sample without funds of funds (labeled as "Hedge Funds"). After applying these filters, our final sample contains 6,147 equity-oriented hedge funds over the sample period 1996 to 2012, of which 2,580 are funds of funds and 3,567 are hedge funds in the seven equity-based strategy categories.

Table 2 summarizes the descriptive statistics of monthly return in excess of the 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 4,503 in 2008, then declines to 3,156 in 2012 following the global financial crisis. During the sample period, the lowest average monthly return is -2.11% in the 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 the sample without funds of funds. Also, we add the time-series of market realized extreme downside returns, measured by minimum daily value of CRSP value-weighted average returns within a month. The graph shows that hedge fund returns are highly volatile and they seem to be highly susceptible to market-wide extreme events such as the Russian debt default in 1998 (collapse of LTCM) and the global financial crisis of 2008 (liquidation of hedge funds of Bear Sterns), in which the minimum market daily returns show substantial downward spikes. The simple time-series average of hedge fund excess returns seems 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 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).[10] Among hedge fund strategies, emerging markets hedge funds have the highest average monthly return, 0.69%, whereas equity market neutral funds 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 a high of 2,580 individual funds in funds of funds to a low of 138 individual funds in convertible arbitrage. Summary statistics of various fund characteristics for our sample funds are displayed in Panel A of Table 3. In our empirical analysis, we consider fund characteristics commonly discussed in 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 notice period (with 30-day as a unit). From the results, we confirm that these summary statistics are similar to and comparable with those in previous hedge fund studies using the TASS database.

3.2 Risk Factors

Prior studies widely document 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). Thus, traditional factors based on linear payoffs might not appropriately capture the hedge fund risk–return tradeoff. Therefore, considering the distinct nature of hedge funds, we adopt the widely used nine-factor model as our benchmark when measuring the 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 include the Carhart (1997) momentum factor (UMD), and Pastor and Stambaugh (2003) market liquidity factor (LIQ).

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[10] Fung and Hsieh (2000) argue 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.

Panel B of Table 3 presents summary statistics of these risk factors. Average market excess return, our main variable of interest, is 0.46% (about 5.71% per year) per month over the period 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 single month; in these months, the hedge fund index also performs badly and 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 with superior future fund performance, along with its significance and persistency. Furthermore, we find evidence suggesting that 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 conducting empirical analysis for individual funds, we run a regression Eq. (13) of the average returns of all funds in our entire sample. With the average returns using the sample including all funds on the period from 1996 to 2012, we get the estimated timing coefficients of -0.025 (t-statistic = -0.81). Similarly, we get the estimated timing coefficients of -0.032 (t-statistic = -1.07) using the average returns of the whole sample excluding funds of funds. Thus, we can conclude that the aggregate hedge funds industry shows positive tail risk timing, that is, the aggregate hedge funds' exposure to the market decreases when market tail risk turns out to be high, but it is not statistically significant in the aggregate level. That is why we focus on the cross-sectional distribution of tail risk timing ability of individual funds.

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 a normality assumption. Since market tail risk grows 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 greater than 2.326, suggesting that some funds display negative tail risk timing, that is, some funds, unusually, tend to increase their exposure to the market when the market tail risk turns out to be high. For the overall sample, the left tails are thicker than the right tails, suggesting that there are more hedge funds reducing their exposure to the market when tail risk appears high than otherwise. In addition, we check the same analysis for funds in each strategy category. From Table 4, we find that almost all categories have thicker left tails.[11]

Overall results indicate that there exist hedge fund managers displaying significant tail risk timing skill according to the conventional critical values under the normality assumption. However, as discussed by Cao, Chen, Liang, and Lo (2013), the above results based on the statistical inference under the conventional normality assumption must be interpreted with caution when 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 an extensive number of

[11] Equity-oriented positions, such as Long/Short Equity and Equity Market Neutral, exhibit thicker left-tail of distribution than right-tail, implying that there are more hedge funds showing positive timing ability to market tail risk in those categories. Surprising thing is that the hedge funds categorized in Event Driven and Convertible Arbitrage have more significant positive tail risk timing than others. Intuitively, hedge fund managers in the Event Driven style show significant timing ability for market tail risk because they are usually professional for market timing. Nevertheless, the results of Convertible Arbitrage seems to be weird. For the Convertible Arbitrage category, funds typically long convertible bonds and short stock so their exposures to market are neutral in normal time. However, at the time of high tail risk in the stock markets, usually accompanied by declines of stock markets, funds taking that kind of position benefit from their short position but convertible bond position declines less than its stock because convertible bond is protected by its value as a fixed-income instrument. Thus, funds categorized in Convertible Arbitrage could show significant timing ability to market tail risk, and this can be managers' ability because there are perverse timers in Convertible Arbitrage category (10.5% of sample show perverse timing coefficients with t-statistic greater than 1.282). Finally, funds in Multi-Strategy category exhibit thicker right-tail than left-tail, in the case of t-statistic with 1.645 and 1.282, but results show opposite in terms of the case of t-statistic exceeding the critical values of 2.5% and 1%. Overall results show that the funds categorized in Multi-Strategy are not good at tail-risk timing, compared to other categories. On the other hand, the funds in Fund of Funds category shows much better timing ability than those in Multi-Strategy. There may be several reasons, but the empirical results might be attributed to the expertise of fund managers. At first, in the case of Fund of Funds, each fund allocate its capital to several other professional hedge funds to be managed, but in the case of Multi-Strategy, each fund chooses strategy depending on outlook and manage its capital in the one house. Thus, strategy professionality, especially timing ability for each strategy, of Multi-Strategy funds is more likely to be less than that of Fund of Funds.

funds, some funds showing no true timing skill appear to have significant t-statistics by chance. Thus, to evaluate managerial skills from a large sample of hedge funds, one of the most important factors is to distinguish managerial skill from pure luck. In this regard, we further implement a bootstrap analysis to check whether the estimated timing coefficients are attributable 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. 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 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 the 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 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, the 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 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 the original top 1 percentile from our hedge fund samples to get the bootstrapped p-value.
5. Repeat steps 1–4 for N iterations to generate the empirical distributions for cross-sectional statistics (e.g., the top 1 percentile) of t-statistics for the pseudo-funds. In our analysis, we repeat the overall steps 3000 times. Finally, for a given set of cross-sectional statistics, calculate bootstrapped empirical p-value as the proportion that the values of the cross-sectional statistic (e.g., the top 1 percentile) for the pseudo-funds from 3000 simulations exceed the actual value of the cross-sectional statistic.

For each 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 tests 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 for the left-tail (positive tail risk timing). For the whole sample, all the empirical p-values of extreme percentiles (from 1% to 10%) suggest 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 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 stemming 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, may 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 a 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 adds economic value to investors. If tail risk timing represents a critical managerial skill, then funds that time well on market tail risk might perform well in the future, and the tail risk timing measure would help to predict future fund performance. The top timer hedge funds show significant positive alphas because they effectively reduce their market exposure when the market-wide uncertainty increases, market exhibits higher volatility, and market often shows downward crashes, at which the option-implied market-wide tail risk increases in turn. Thus, we assume that tail risk timing represents a valuable managerial skill, and then conduct two kinds of analysis to determine the 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 values of net-of-free fund returns over the past 24-month estimation period by the tail risk timing model, Eq. (13). Then, we construct 10 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 3-, 6-, 9-, and 12-month holding periods, and we repeat this process.[12] Next, we calculate average monthly excess returns and then evaluate risk-adjusted performance for each of the 10 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.[13]

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 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 all categories except funds of funds. Panel A shows the results 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 their performance in the future. 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 a 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 remains 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 holding periods from 6 to 12 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. Further, 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 6, 9, and 12-month holding periods. As in the three-month holding period, the difference in subsequent performance after adjusting for the nine factors is even greater both in magnitude and statistical significance. For instance, for a 12-month holding period, the risk-adjusted spread is 0.55% per month (6.84% per year).

[12] We decide the minimum holding period is three months because the average lock-up period for our sample funds is close to three months (actually 76 days).

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

That is, top tail risk timing funds outperform bottom timers by about 5–7% per year subsequently on a risk-adjusted basis. This outperformance of top timers over bottom timers and the monotonicity of subsequent performance is also shown in the only hedge fund sample without funds of funds. These results are shown in Panel B of Table 6.

The economic value of tail risk timing is observed more directly from Figure 3. We additionally check the full visualized distribution of performance of decile portfolios. Figure 3 plots out-of-sample alphas of decile hedge fund portfolios within both the 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 declines. 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 the three-month holding case, top tail risk timing funds exhibit an average alpha four to five times greater than that of bottom timing funds, and this difference increases as holding periods increase.

Thus far, we investigate the relationship between tail risk timing skill and future hedge fund performance using univariate portfolio-level analysis. However, in portfolio-level analysis, it is difficult to control for other factors simultaneously. Meanwhile, the literature suggests 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 fund timing skill, simultaneously controlling for fund characteristics and investment style 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 Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor for each hedge fund with at least 24 months of 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 a time-series moving average of monthly excess returns and alphas for 3 to 12 months of all individual hedge funds and run the following specified regressions:

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

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 the past 24-month rolling estimation window. $X_{i,t-1}$ represents various fund characteristics, including log of fund age, log of AUM, management fee, incentive fee, high-water mark dummy, minimum investment, lockup period, and redemption notice period, along with 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, the regression results provide evidence of a negative and significant relation between timing skill and future fund returns. In detail, 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 from multivariate analysis show that the tail risk timing skill of hedge funds remains a significant predictor of future excess returns or nine-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 the 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 tail risk timing skill reflects crucial managerial skill for hedge funds and can be an important source of hedge fund alpha. We also show that this timing skill persists over time in out-of-sample testing. The results are consistent with the literature that documents that hedge fund alphas significantly persist over time (e.g., Jagannathan, Malakhov, and Novikov, 2010; Cao, Chen, Liang, and Lo, 2013). Finally, the economic value of tail risk timing of hedge funds is robust to other fund characteristics that may affect future performance and hedge funds. In the next subsection, we simply check the persistency of the 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 a similar spirit to 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 a 12-

month tail-risk timing coefficient using the same timing model Eq. (13) over the next 12 months and show the simple average of those post-timing coefficients within decile portfolios.

Figure 5 presents the results of portfolio 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 out-of-sample timing coefficient of -0.081 for a 12-month post-formation period, while the bottom 10% timing funds (bottom timers) have a subsequent timing coefficient of -0.014 for the same period. The spread between the timing coefficient of the top and bottom timers is 0.068 and 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 in their behavior to perform well (worse) in the future. This result is consistent with the hedge fund literature that 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 consistent with prior results showing that 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 on whether a specified group of hedge funds sample causes biases to our main inferences on tail risk timing ability. In detail, it is possible that our results on tail risk timing are driven by use 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 tail risk timing is robust to other potential factors.

5.1 Subsample Analysis

This subsection tests for sample biases that might affect the inference on tail risk timing. First, as noted by Lo (2008), use 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 market shocks, when market tail risk becomes high. Thus, one might wonder whether the reduction of market exposure under sudden market shocks or increases in market tail risk merely reflect responses to a deterioration in funding liquidity because prime brokers cut funding or increase borrowing costs. Hence, we repeat our analysis using a subsample of funds that use no leverage and that use leverage. If the changes in funds' market exposure to sudden shifts in market tail risk are caused by fluctuation of leverage and 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 the future performance.

Second, apart from broker-dictated changes in leverage, external funding constraints can also be caused by investor redemptions. Under a similar mechanism to changes in leverage, changes in funds' market exposure can be caused merely by funding constraints due to investor redemption. This is because fund managers need to unwind their positions and decrease their market exposure when investors withdraw their capital (e.g., Khandani and Lo, 2007). For example, during the 2007-08 global financial crisis , many hedge funds experienced heavy and sudden investor redemption, 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 a redemption notice period of 60 days or longer. A longer redemption frequency blocks sudden investor redemptions, and this provision is especially effective during extreme market conditions such as a high tail risk market. Also, a longer redemption notice period allows fund managers to have more time to adjust positions to meet sudden investor withdrawals, and this provision also reduces funding constraints stemming from the impact of investor redemptions. In this regard, we are concerned about the possibility that changes in funds' market exposures are responses to investor redemptions, not 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, as trading activities of small funds are more unlikely to affect market conditions than others. To do so, we classify a fund as a small fund if its total AUM is less than $50 million (or less than $150 million). If the changes in fund 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 subsample: funds that use leverage or not, that have redemption frequency equal or greater than one quarter, that impose redemption notice periods equal to or greater than 60 days, and that have AUM below $50 or $150 million. For brevity, we report only the results of bootstrap analyses for all funds, hedge funds (sample without funds of funds), and funds of funds.[14] The overall results in Table 8 suggest that regardless of use of leverage, whether the redemption frequency is low or not, and fund size, all subsamples show significant tail risk timing, and their timing ability is not attributable to pure luck. All p-values on the columns denominated as bottom t-statistics for timing skill are close to zero. Although external leverage and investor redemption can affect funds' market exposure, they do not reflect managerial skill. Also, our results are not driven by large fund trading that could impact market conditions.

Furthermore, we conduct a simple univariate portfolio analysis using six subsamples. To conserve space, we report only 12-month holding period nine-factor alphas of decile portfolios based on 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 the top timer portfolio and the difference between the top and bottom timers is also significant. These results add to the robustness of our results arguing that tail risk timing is an important managerial skill. In summary, none of our findings qualitatively change after we conduct various alternative subsample analyses, suggesting that our main inferences on the tail risk timing ability of hedge funds stem mostly from managers' superior timing skill, not from changes in leverage, sudden investor redemption requests, or trading impact of large funds.

5.2 Sub-Period Analysis

[14] Detailed results are available upon request.

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

Panel A of Table 10 reports the empirical results for bootstrap analysis with a sample of pre-crisis periods. Consistent with Table 5, we report 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 is unlikely to be attributable to random chance or pure luck. Also, we report the results of univariate portfolio analysis in Table 6. Panel B of Table 10 reports the average performance of decile equal-weighted hedge fund portfolios for pre-crisis periods. We display both 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 3 to 12 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 tail risk timing by hedge funds remain unchanged even after excluding the 2008–2009 financial crisis period from our sample, and that this represents evidence that our main findings are not driven by sample bias.

5.3 Controlling for Other Timing Skills

In our main analyses, our baseline timing model focuses mainly on the strategic 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, previous studies document 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 the 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 the market, such as liquidity or volatility and simultaneously changes in market tail risk implied by options, then these 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 baseline option-implied tail risk timing model, as in the following specification:

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

where Vol_{t+1} is 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 the Pastor-Stambaugh (2003) market liquidity measure, and 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 estimate 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 controlling 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 the 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 result also holds for the 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 even after controlling for other dimensions of timing skill. Interestingly, the average monthly excess return spread and difference in alphas between the top and bottom timers becomes stronger than before. In summary, the overall results, shown 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 funds. 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 the 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 periods. Table 12 summarizes the results of two-way portfolio analysis. To conserve space, we report only the results for 9 portfolios out of 15 (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), the spreads between top timer (Portfolio1) and bottom timer (Portfolio5) for option-implied tail risk are 0.31%, 0.27%, and 0.35% for three liquidity timing groups, respectively, after controlling for nine factors, and these spreads are all statistically and economically significant. Except for certain 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 the stock market, implying that tail risk timing is a crucial managerial skill of hedge fund managers, determining the future performance of funds.

5.4 Controlling for Other Managerial Skills

Thus far, we explore a new dimension of hedge fund manager skill: the ability to time market tail risk implied by options markets, 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 these skills. In this regard, 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 that 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 markets suggested by Sun, Wang, and Zheng (2014).

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

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

To perform this robustness test, first we measure two other managerial skills. For each fund, R-squared (*RSQ)* is measured by rolling R-squared from a regression of excess returns of hedge funds on the Fung and Hsieh (2004) seven factors using an estimation period of two years; also, 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 aggregate hedge fund returns are below the median level over the past 24-month window. Then, for each hedge fund with at least six observations over the 12 months, we take the time-series average of fund returns to get the *Downside-Returns* measure, as follows:

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

After constructing these measures of managerial skills, *RSQ*, and *Downside-Returns*, we examine whether the predictive power of tail risk timing skill for future hedge fund performance remains even after controlling for the 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:

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

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

The results are reported in Table 13. To conserve space, we report only 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 skills without characteristics control over the different holding periods, and Panel B reports those with fund characteristics control. Throughout the results, our tail risk timing skill remains economically and statistically significant. Also, in terms of alpha, *RSQ* and *Downside-Returns* have significant predictive ability for future hedge fund performance, as previous studies document. To sum up, the overall results in Table 13 suggest that our tail risk timing skill findings for hedge funds have strong economic meaning for managerial skill and are robust to other managerial skill proxies likely to be associated with tail risk timing ability.

6. Conclusions

This paper examines whether hedge funds, among the most professional and sophisticated asset managers, have market tail risk timing ability. The literature has focused on fund managers' timing ability with respect to market returns, and some studies document 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, 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 information extracted from options markets, because it is well known that options prices contain 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 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, using 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 on a 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 use of controls for other market dimensions of timing ability and other types of hedge fund managerial skills. Overall, our findings contribute to the academic literature on the managerial skills of hedge funds, especially timing ability, and emphasize the importance of incorporating market tail risk in investment decisions for practitioners and investors.

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

This table presents a correlation matrix of four option-implied measures: risk-neutral skewness (RN Skew), risk-neutral kurtosis (RN Kurt), slope of the implied volatility smirk for out-of-the-money S&P 500 put options (S&P Slope), 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 characteristics of the market portfolio and the option-implied tail risk measure (Op-Tail). Panel A reports the Pearson correlation matrix of the above four measures. Details on the construction and description of these four option-implied measures and Op-Tail are described in Section 2-2. Panel B reports estimates of monthly regression results of the characteristics of market portfolio on the change of the Op-Tail. We conduct monthly regression; $Tail\ (Market)_{t+k} = constant + b_1 * Tail\ (Market)_t + b_2 * \Delta(Op - Tail)_{m,t} + e_{t+k}$, 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 the S&P 500 Index. When k is equal to zero, we regress realized market returns on the only constant and contemporaneous $\Delta(Op - Tail)$. We report only estimated b_2 coefficients for each k from -4 to 4 and Newey–West (1987) t-statistics using 12 months of lags. Significance at the 1%, 5%, and 10% levels is indicated by $***$, $**$, and $*$, respectively. The sample period is from January 1996 to December 2012.

Panel A. Correlation Matrix

	RN Skew	RN Kurt	S&P Slope	Indi Slope
RN Skew	1.00			
RN 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 Fund 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 summarizes 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 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, high-water mark dummy, minimum investment, leverage usage dummy, log of fund age, log of fund size (log of AUM), lockup period, and redemption notice period in months. Panel B presents the Fung-Hsieh (2004) seven factors, namely, excess market return (MKTRF), size factor (SMB), monthly change in 10-year Treasury constant maturity yield (YLDCH), monthly change in Moody's Baa yield less 10-year Treasury constant maturity yield (BAAMT), and three trend-following factors on bonds (PTFSB), foreign exchange (PTFSFX), and commodities (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.

Characteristics	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
Highwatermark	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. Summary 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 Tail Risk Timing Coefficients

This table reports cross-sectional distribution of t-statistics of the tail risk timing coefficient for all funds and each strategy category. Category "Hedge Funds" contains all funds except for those included in "Fund of Funds." We report 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 the 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 excess return for fund p in month $t+1$. MKT_{t+1} is excess return on the market portfolio in month $t+1$. $\Delta(Op - Tail)_{t+1}$ is 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. t-statistics are heteroscedasticity consistent. The sample period is from January 1996 to December 2012.

		Percentage of 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. For all strategies, we report t-statistics of tail risk timing coefficients estimated from actual fund returns for indicated cross-sectional statistics (e.g., 1,3,5, and 10[th] percentiles) and present the corresponding empirical p-values from bootstrap simulations. The number of iterations for empirical distribution of t-statistics is 3000. 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 a 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-months. For each portfolio and top-minus-bottom timer spread, we report both monthly excess returns and nine-factor alphas (in percent), including Fung-Hsieh (2004) seven factors, Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor, across different holding periods. Alpha is defined as returns net of what is attributable to factor exposures. That is, 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 parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% levels is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Excess Returns				Nine-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-months, 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 the 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 the 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 a 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. t-statistics are based on Newey–West (1987) standard errors with three lags. Significance at the 1%, 5%, and 10% levels is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Dependent Variable							
	Excess Returns				Nine-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 and those that do not, and those that have redemption frequency equal to or greater than one quarter, that impose redemption notice periods equal to or greater than 60 days, and that have assets under management (AUM) below \$50 million or \$150 million. Category "Hedge Funds" contains 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 a normality assumption. For funds with at least 24 monthly observations, we estimate the 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 excess return for fund p in month t+1. MKT_{t+1} is excess return on the market portfolio in month t+1. $\Delta(Op - Tail)_{m,t+1}$ is 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. 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 One 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 Greater 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 million										
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 million

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 one quarter (denoted as sample (3)), that have redemption notice periods equal or longer than 60 days (denoted as sample (4)), that have assets 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 a 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 space, we report only results based on portfolios held for 12-month periods. For each portfolio and top-minus-bottom timer spread, we report our benchmark nine-factor alphas (in percent), including Fung-Hsieh (2004) seven factors, Carhart (1997) momentum factor, and Pastor-Stambaugh (2003) liquidity factor. Alpha is defined as returns net of what is attributable to factor exposures. That is, the alpha is estimated by regression of decile portfolio returns on the above nine factors. t-statistics based on Newey–West (1987) standard errors with three lags are in parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% levels is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	12-month Holding Nine-factor 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 sub-period 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 the 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 excess return for fund p in month t+1. MKT_{t+1} is excess return on the market portfolio in month t+1. $\Delta(\mathrm{Op} - Tail)_{t+1}$ is 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 nine-factor alphas of 10 equal-weighted portfolios and top-minus-bottom spread of hedge funds constructed based on fund tail risk timing skill across various holding periods. t-statistics based on Newey–West (1987) standard errors with three lags are in parentheses. Significance of top-minus-bottom timer spread at the 1%, 5%, and 10% levels is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2007.

Panel A. Bootstrap Analysis for 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 Pre-crisis Period (1996-2007)								
	Excess Returns				Nine-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. 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 the following tail risk timing model with controls for market, volatility, and liquidity timing.

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

where $r_{p,t+1}$ is excess return for fund p in month t+1. MKT_{t+1} is excess return on the market portfolio in month t+1. $\Delta(Op - Tail)_{m,t+1}$ is monthly change of option-implied tail risk measure in month t+1, described in Section 2-2. Vol_{t+1} is market volatility in month t+1 as measured by 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 the 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. 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 nine-factor alphas of 10 equal-weighted portfolios and top-minus-bottom spread of hedge funds constructed based on funds' tail risk timing skill across various holding periods. t-statistics based on Newey–West (1987) standard errors with three lags are in 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				Nine-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 the 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 excess return for fund p in month t+1. MKT_{t+1} is 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_{t+1}^2), 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 the 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. At the beginning of each 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-months. For each 15 portfolio and top-minus-bottom timer spreads (Portfolio1 – Portfolio5), we calculate nine-factor alphas (in percent) consistent with previous analysis. Columns named "Low," "Middle," and "High" indicate the bottom, middle, and top portfolios based on market, liquidity, or volatility timing coefficients, and "Portfolio1 (Portfolio5)" is the top timer (bottom timer) portfolio, consisting of funds with lower (higher) timing coefficients to option-implied market tail risk. To conserve space, we omit the results of Portfolio2 and Portfolio4. t-statistics based on Newey–West (1987) standard errors with three lags are in 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 the 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-squared) suggested by Titman and Tiu (2011) and downside returns (Downside-Returns) discussed by Sun, Wang, and Zheng (2014). Details on the construction and description of these two measures are summarized in Section 5-4. Control variables are the same as in Table 7. For brevity, we report only 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, downside returns, and both proxies simultaneously are displayed in Panels A and B. t-statistics are based on Newey–West (1987) standard errors with three lags. Significance at the 1%, 5%, and 10% levels is indicated by ∗∗∗, ∗∗, and ∗, respectively. The sample period is from January 1996 to December 2012.

	Dependent Variable							
	Excess Returns				Nine-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 "Op-Tail" and realized market tail after 1-month. Op-Tail is constructed as the first principal components of risk-neutral skewness (R.N. Skew), risk-neutral kurtosis (R.N. Kurt), 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 these measures are summarized in Section 2-2. The realized market tail is measured as the minimum daily return of CRSP value-weighted market returns, including dividends, for a corresponding month. To emphasize comparison, the monthly series of the minimum daily return is scaled to have mean zero and variance 1. The sample period is from January 1996 to December 2012.

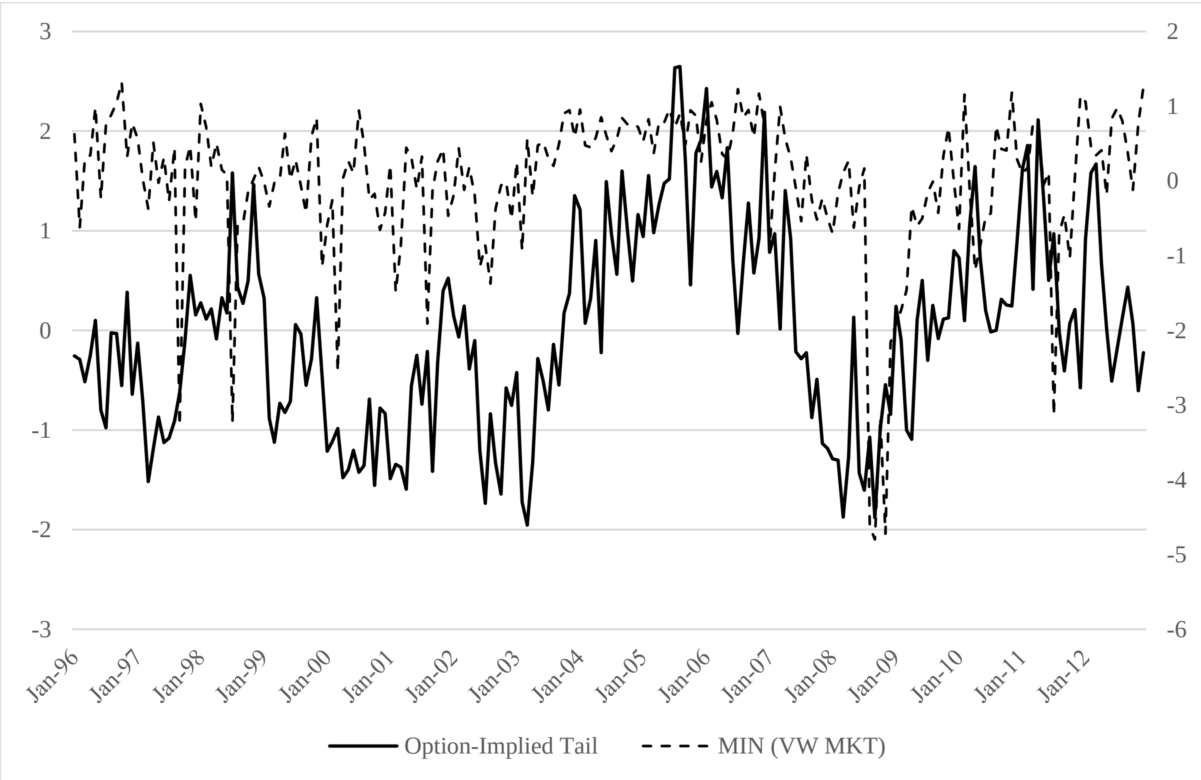
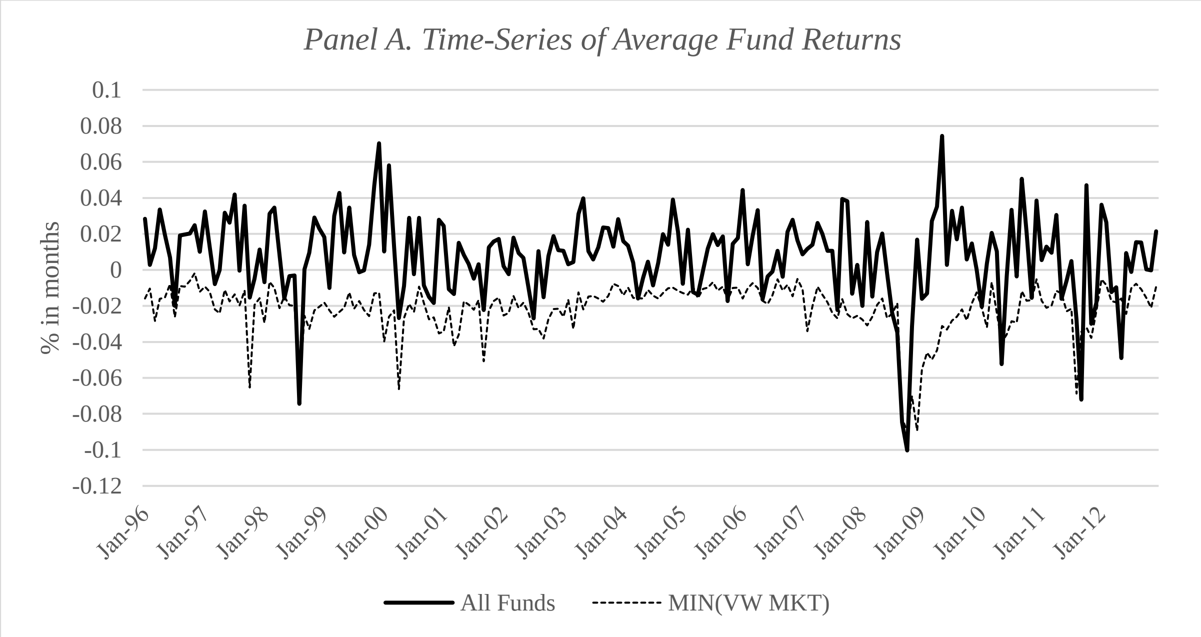


Figure 2. Times-Series Average of Aggregate Hedge Fund Returns

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 return is measured as the minimum daily return 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 fund returns except for "Fund of Funds." The sample period is from January 1996 to December 2012.



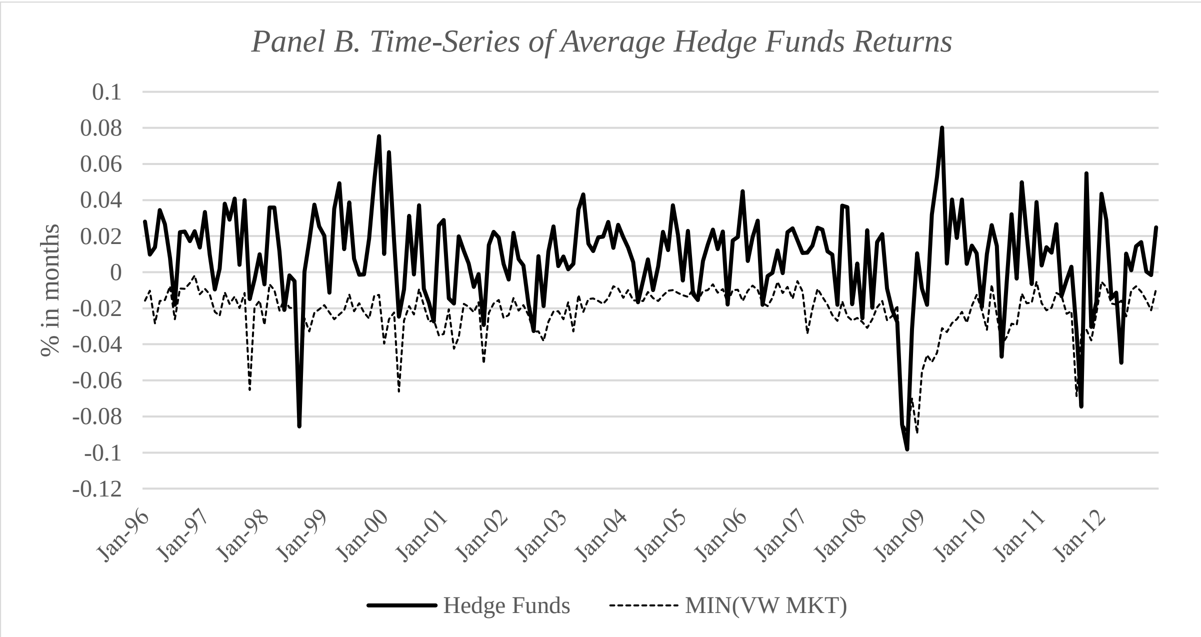


Figure 3. 12-Month Holding Period Out-of-Sample Alphas for Decile Portfolios

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 a 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 a 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.

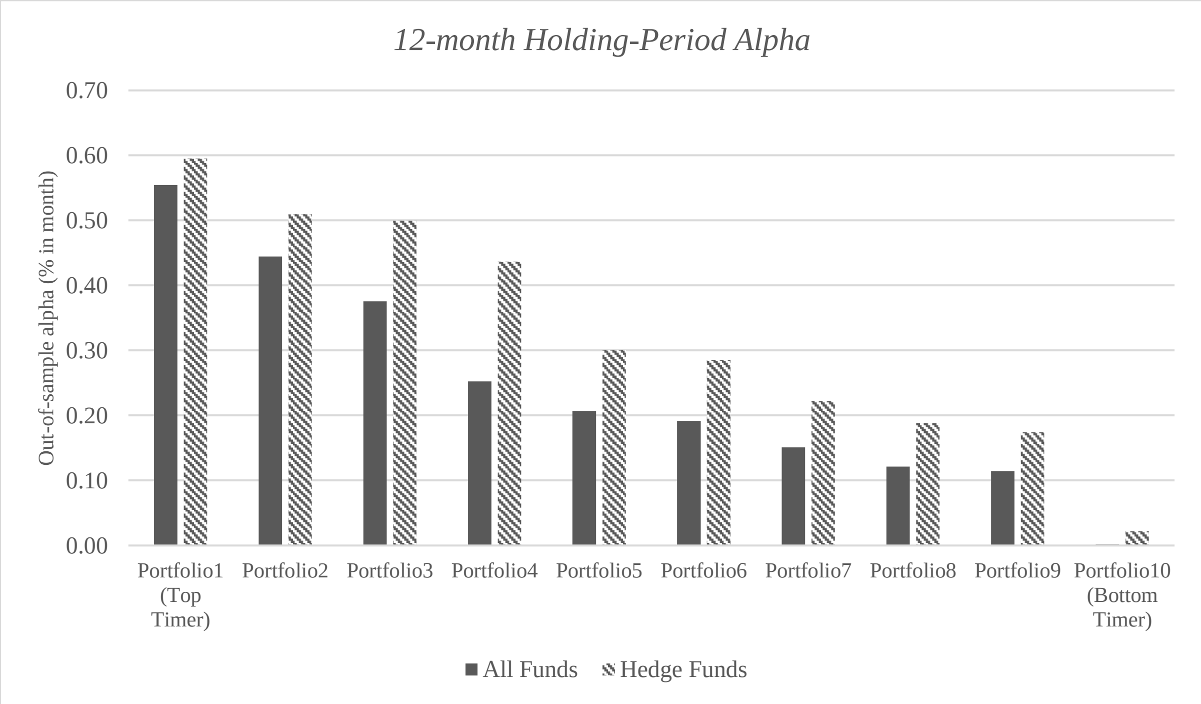
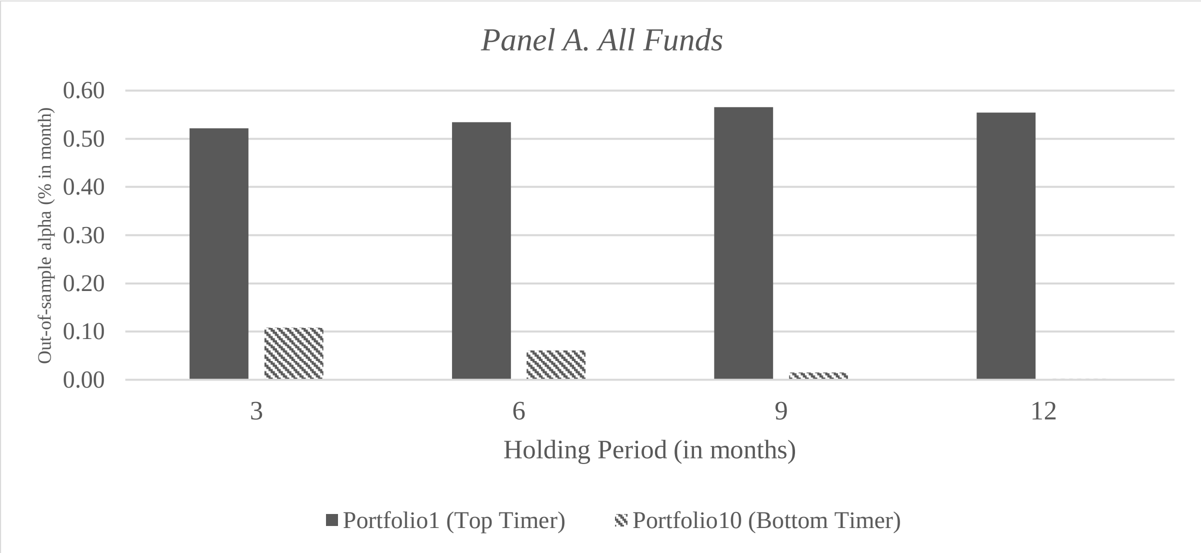


Figure 4. Out-of-Sample Alphas for Top versus Bottom Timer Portfolios

This figure depicts out-of-sample alphas for portfolios consisting of top versus bottom timing funds for a holding period of 3, 6, 9, or 12 months. In each month, for each fund with at least 18 monthly observations in the past 24 months, we estimate a 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.



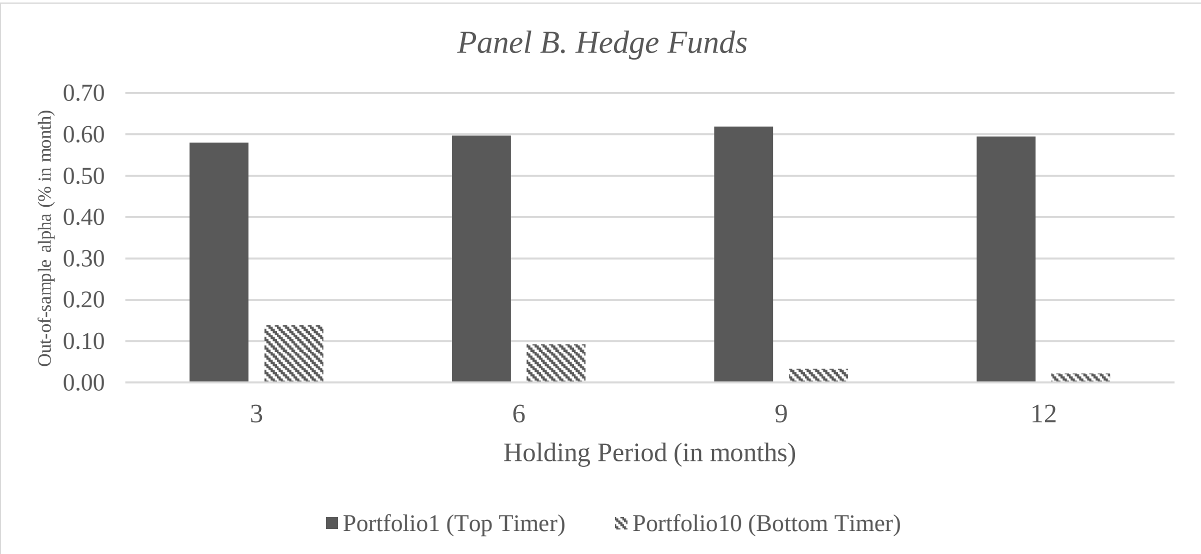


Figure 5. Persistency of Tail Risk Timing

This figure displays 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 a tail risk timing coefficient and assign all funds into 10 portfolios that are rebalanced each month based on the estimated coefficients. We then estimate the timing model Eq. (13) for each hedge fund, composing decile portfolios using 24-month holding periods to evaluate fund managers' subsequent timing skill and display an average of the estimates across decile portfolios. The sample period is from January 1996 to December 2012.