# Short Selling Risk and Hedge Fund Performance

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Abstract: Hedge funds, on average, outperform other actively managed funds. However, hedge fund managers often use trading strategies that are not used by other managed portfolios, and thus they bear unique risks. In particular, many hedge funds use short selling. I construct an option-based measure of short selling risk as the return spread between the decile of stocks with low option-implied short selling fees and the decile of those with high fees. I find that hedge funds that are significantly exposed to short selling risk outperform low-exposure funds by 0.45% per month on a risk-adjusted basis. However, there is no such relation for mutual funds that invest primarily on the long side. The results highlight that a significant proportion of abnormal performance of hedge funds is compensation for the risk they take on their short positions.

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*There is no "alpha." There is just beta you understand and beta you do not understand, and beta you are positioned to buy versus beta you are already exposed to and should sell.*

– John Cochrane, AFA 2011 Presidential Address

## 1. Introduction

Compared to traditional actively managed portfolios, hedge funds deliver superior alphas (Liang 1999; Stulz 2007).[1] While the superior performance of hedge funds can result from their ability to exploit flexible investment strategies and unconventional investment assets (Fung and Hsieh 1997), studies have shown that at least part of their superior performance is attributable to risk premia associated with risk factors not captured by standard benchmark models.[2] As a group of sophisticated arbitrageurs, hedge funds often use short selling as an important investment tool to generate arbitraging profits. Thus, in this study, I investigate hedge funds' exposure to short selling risk. My primary finding is that hedge funds' exposure to this risk significantly and positively relates to their future returns, after controlling for exposures to other documented risk factors. In contrast, for mutual funds that mainly hold long-equity positions, there is no such relation. In other words, part of the superior performance of hedge funds stems from a risk premium resulting from their short selling strategies.

Finance theories often assume that short selling is risk free and costless (e.g., Markowitz 1952; Sharpe 1964; Ross 1976). However, a growing literature emphasizes that shorting a stock is risky. The dynamic risks associated with short selling—the risk of future recalls and of changing

[1] Liang (1999) documents that the efficient frontier of hedge funds surpassed that of mutual funds. In addition, a survery by Stulz (2007) shows that hedge funds produce a 3% to 5% annualized alpha.

[2] The literature has documented that hedge funds exhibit option-like returns. For example, when analyzing hedge fund returns, Fung and Hsieh (1997, 2001), Mitchell and Pulvino (2001), and Agarwal and Naik (2004) propose risk factors to account for the risks associated with hedge funds' option-like dynamic trading strategies. In addition, recently, Bali et al. (2014) report that hedge fund returns relate significantly to loadings on macroeconomic risk factors because hedge funds aggressively pursue opportunities arising from changing economic circumstances.

equity loan fees—are significant risks that short sellers bear (e.g., D'Avolio 2002, Dreslter and Drestler 2018, and Engelberg et al. 2018).[3] Shleifer and Vishny's (1997) model predicts that, when arbitrage is riskier, stocks exhibit greater mispricing and average returns to arbitrage are larger. In line with the work of Shleifer and Vishny (1997), the model of D'Avolio (2002) predicts that shorting overpriced stocks is risky. In particular, D'Avolio (2002) shows that stock loan fees increase and share availability decreases as a function of the heterogeneity in beliefs of different investors, and a large literature suggests that overpricing increases as a function of heterogeneity in beliefs (e.g., Miller 1977). Thus, stocks that are more overpriced are also riskier to short. That is, they are more likely to be recalled by lenders or to experience significant increases in lending fees. Consequently, arbitrageurs bear a larger risk when shorting these stocks. Building on D'Avolio (2002), Drechsler and Drechsler (2018) show that arbitrageurs demand risk premium for bearing the risk associated with short selling. By shorting overpriced stocks, arbitrageurs deviate from holding the aggregate market portfolio and thus are more exposed to the short selling risk associated with those stocks. As long as arbitrageurs are not risk neutral, they demand a risk premium.

Short selling risk could be important to the hedge fund industry for two reasons. First, by betting against overpricing, fund managers often hold concentrated short positions and thus their short selling risk is unlikely to be diversified away.[4] Second, Shleifer and Vishny (1997) predict that arbitraging—in this case, short selling—is particularly risky for the portfolio management industry due to an agency problem. Specifically, because investors tend to withdraw capital from hedge funds with poor performance (e.g., Sirri and Tufano 1998), if the overpriced stocks that

[3] Under current regulations, equity lenders in the United States maintain the right to recall or cancel an equity loan at any time. When recalls occur, stocks lenders will take their shares back before the short sellers realize arbitrage profits.
[4] For example, in 2012, hedge fund manager Bill Ackman made a $1 billion short bet against Herbalife, comprising a large position in his fund's portfolio.

hedge funds bet against are recalled by lenders before their prices return to the fundamental value, the funds are at a greater risk of capital outflows resulting in losses on their short positions. Collectively, these theories suggest a positive cross-sectional relation between hedge funds' exposure to short selling risk and their future performance.

To test this conjecture, I use option-implied loan fees — the expected (future) equity lending fees over the life of the option — to measure short selling risk. Engelberg et al. (2018) argue that a share recall can be considered as an extremely high equity loan fee. Therefore, this measure captures the D'Avolio's (2002) theoretical construct of the dynamic risks perceived by short sellers — the risk of future recalls and increases in future loan fees. In addition, the use of option-implied loan fees as a proxy allows me to perform my analyses over a long sample period, spanning from January 1996 through December 2015.

I construct a market-based short selling risk factor on the basis of option-implied loan fees. Specifically, for each month starting from January 1996, I form equal-weighted decile portfolios of stocks sorted by option-implied loan fees and then hold these portfolios for one calendar month. The short risk factor is the return spread between the decile of stocks with low option-implied shorting fees (bottom decile) and the decile with high option-implied shorting fees (top decile). The short risk factor yields an average excess return of 1.54% per month and a Fama-French-four factor alpha of 1.59%, which cannot be attributed to conventional risk factors but rather be viewed as the return premium to short selling risk.

I perform my empirical analyses using a sample of 5,388 U.S. equity-oriented hedge funds over the period from January 1996 to December 2015.[5] I start by measuring a hedge fund's short

[5] Because I focus on short selling risk pertaining to U.S. equity markets, my sample includes U.S. equity-oriented hedge funds in seven investment strategy categories: convertible arbitrage, event driven, equity market neutral, funds of funds, long/short equity, dedicated short bias, and multi strategy.

risk exposure as the covariance of its returns with the short risk factor. Specifically, for each hedge fund, I run a time-series regression each month of the hedge funds' excess returns on the short risk factor over the previous 36 months, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. The coefficient estimate on the short risk factor is the fund's short risk exposure.

I use both portfolio-level analyses and Fama and MacBeth (1973) cross-sectional regressions to examine the effect of hedge funds' short risk exposures in predicting their performance. First, when hedge funds are sorted into deciles by short risk exposures, the top decile, on average, outperforms the bottom decile by 0.44% (*t*-statistic = 2.68) over the next month. After controlling for standard risk exposures, the spread in alpha is similar in magnitude, 0.45% (*t*-statistic = 2.78) per month. Second, using a Fama and MacBeth (1973) regression framework, I continue to observe a positive relation between a hedge fund's short risk exposure and its next month's performance after controlling for fund characteristics and investment style. These findings suggest that the exposure to short selling risk is an important determinant of cross-sectional hedge fund returns.

I perform a number of tests to corroborate and extend my primary findings. First, I examine the relation between hedge funds' short risk exposures and various fund characteristics. I find that funds that charge higher incentive fees and those that adopt high-water-mark provisions have larger exposures to short selling risk, consistent with the notion that managerial incentives spur risk taking. In addition, I find that funds with longer lock-up periods or redemption notice periods have larger exposures to short selling risk, consistent with these restrictions protecting hedge funds from forced liquidations and thus increasing their risk appetites.

Second, I analyze the effect of short risk exposure among different investment styles of hedge funds. I classify hedge funds into four groups according to their investment strategy (directional arbitrage, non-directional arbitrage, multi-strategy, and funds of funds) and find that short risk exposure relates positively and significantly to hedge fund returns only for directional funds. This finding is consistent with the notion that some directional funds are designed to profit from arbitrage opportunities through short selling.

Third, I examine the return spread between the top and bottom short-risk-exposure deciles over different holding periods, ranging from 3 to 12 months. I find that the return spread between the top and bottom short-risk-exposure deciles declines over time. In particular, the top decile outperforms the bottom decile for up to six months after portfolio formation, and only 65% (41%) of the hedge funds in the top decile remain in the same decile after 6 (12) months. These results are consistent with the dynamic nature of hedge fund trading strategies leading to time-varying short risk exposures.

Fourth, I explore whether the performance of hedge funds with high short risk exposure stems from fund managers' abilities rather than just exposure to short selling risk. First, I use the extent to which hedge fund returns can be explained by systematic risk factors as a proxy for stock picking ability, as Titman and Tiu (2011) show that funds managed by skilled managers have smaller systematic risk-return associations. Second, because arbitrage profits vary with market conditions, managers with market timing ability can adjust their short positions accordingly to gain larger profits from short selling. I examine three market characteristics that skilled managers have been shown to be able to time: return, volatility, and liquidity (Chen and Liang 2007; Cao et al. 2013). I find that hedge funds with larger short risk exposure, on average, are associated with lower systematic risk-return associations, suggesting that managers of these funds are better stock pickers.

However, I find no evidence that hedge funds with larger short risk exposure are better at market timing. Next, I perform double sorts by first sorting hedge funds into quintiles based on systematic risk-return associations and then sorting into quin+tiles based on short risk exposure. For each quintile of systematic risk-return associations, the spreads in returns and alphas between the top and bottom short risk exposure quintiles are both statistically and economically significant. These findings suggest that hedge funds' superior performance cannot be fully explained by managers' ability and that a considerable component of performance stems from compensation for short selling risk.

This paper makes several contributions. First, it contributes to the literature examining hedge fund returns and underlying risk factors (e.g., Fung and Hsieh 1997, 2001; Mitchell and Pulvino 2001; Agarwal and Naik 2004; Sadka 2010; Bali et al. 2012, 2014; Jiang and Kelly 2014; Chen et al. 2016). By examining short selling risk, a previously unexplored risk, my study provides evidence that a significant proportion of hedge funds' superior performance is compensation for short selling risk. Evaluation of hedge fund performance is an important but challenging issue for finance academics and practitioners because accurate inferences about hedge fund performance depend on the appropriateness of the benchmark model used. The evidence here highlights the importance of accounting for short selling risk when evaluating hedge funds.

Second, my study contributes to the literature on limits to arbitrage. The theoretical model of Shleifer and Vishny (1997) predicts that stocks that are riskier to arbitrage are more likely to be mispriced and offer higher returns to arbitrageurs. In the case of short selling, a recent empirical study by Engelberg et al. (2018) shows that stocks with high short selling risk exhibit greater overpricing and that arbitraging these stocks is rewarded with higher expected returns. Along the same lines, Drechsler and Drechsler (2018) empirically show that abnormal returns to stocks with high lending fees reflect the premium that short sellers require for bearing the risk of their short positions. Extending these studies, my work provides direct evidence that short selling risk can predict returns to arbitrageurs.

Finally, my study advances the understanding of the performance of short sellers. As shown in the literature, short interest is highly informative about future returns (e.g., Senchack and Starks 1993; Asquith et al. 2005; Cohen et al. 2007). Several studies find evidence suggesting that short sellers earn higher returns due to either their information advantage or superior information processing (e.g., Boehmer et al. 2008; Engelberg et al. 2012; Christophe et al. 2004; Choi et al. 2017). My study complements these findings by documenting that part of short sellers' superior performance represents a risk premium for short selling.

The rest of the paper proceeds as follows. Section 2 develops the theoretical motivation. Section 3 discusses the sample, data, and variable measurement. Section 4 reports the empirical findings. Section 5 shows a series of robustness checks. Section 6 concludes.

## 2. Theoretical development and hypotheses

If there is no free lunch in financial markets (Friedman 1975), then higher investment returns must come from bearing higher risk. Whereas arbitrage is viewed by some as a risk-free return in an inefficient market, the classic work of Shleifer and Vishny (1997) suggests that arbitrageurs are rewarded for bearing risk. Lowenstein (2000) draws an analogy between arbitraging and "picking up nickels in front of bulldozers." D'Avolio (2002) demonstrates that in addition to the traditional risks faced by other traders, short sellers face significant uncertainties about future equity lending conditions—the risk of recalls or the risk of increasing stock lending fees.[6]

Consistent with predictions in models of limits to arbitrage (e.g., Shleifer and Vishny 1997), D'Avolio (2002) predicts that a largely overpriced stock is more likely to be recalled by lenders, creating a large risk to arbitrageurs. The low subsequent returns of this stock are compensation earned by arbitrageurs for the short selling risk they bear. Specifically, the more a stock is overpriced, the more it is affected by noise traders and likely to further move away from the fundamental value (e.g., DeLong et al. 1990). Because stock price reflects the opinions of the most optimistic investors (Miller 1977), as the price moves further away from its fundamental value, the lender's valuation of the borrowed stock is more likely to fall below the marginal investor's valuation (or market price). Consequently, the lender will recall (or cancel) the loan to profit from selling the temporarily overpriced shares or to re-lend them at a higher loan fee. In either case, the recalled arbitrageur must cover her short position by buying back the shares and returning them to the lender or re-establishing the short position at a higher loan fee. As a result, the arbitrageur faces larger potential losses when shorting a stock with greater overpricing. As the price of the overpriced stock drops to the fundamental value in the future, the arbitrageur, in return, is rewarded with a larger arbitrage profit.

Building on D'Avolio (2002), Drechsler and Drechsler (2018) develop a multi-period model that predicts that arbitrageurs demand risk premium for bearing the risk associated with shorting overpriced stocks. Overpriced stocks receive the common stock from shorting, e.g., those stocks are more likely to experience an increase in future loan fees and to be recalled by lenders. By shorting overpriced stocks, arbitrageurs bear non-diversified shorting risk by deviating from

[6] Under current regulations, equity lenders maintain the right to recall or cancel an equity loan at any time.

holding the market portfolio. In their model, arbitrageurs (or short sellers) are the marginal investor of overpriced stocks. As long as they are not risk neutral, they demand a risk premium. Because this risk is on the short side, a larger premium means a more overpriced stock. In the same vein, Cho (2019) shows that more mispriced stocks attract more arbitrage and covary more with common shocks from the act of arbitrage by institutional arbitrageurs, generating "arbitraging-driven" betas.

In line with these theoretical predictions, Engelberg et al. (2018) show empirically that stocks with high volatility of equity lending fees, a proxy for the short selling risk, exhibit greater overpricing and lower average subsequent returns. In addition, Drechsler and Drechsler (2018) construct a short risk factor based on the level of historical equity loan fees and find that short selling risk accounts for a significant proportion of eight anomalies returns.

Short selling risk should be relevant to hedge funds for at least two reasons. First, many hedge fund managers use short selling extensively to bet against overvalued stocks. In doing so, they often run portfolios with concentrated short positions, and thus short selling risk is unlikely to be diversified away.[7] Second, Shleifer and Vishny (1997) predict that arbitraging is particularly risky for the portfolio management industry. Investors tend to withdraw capital from hedge funds with poor performance (e.g., Sirri and Tufano 1998). Thus, if the overpriced shares that hedge funds bet against are recalled by lenders before their prices return to the fundamental value, the funds face a larger risk of outflows.

[7] For instance, Ben-David et al. (2012) cite a Goldman Sachs report stating that hedge funds took 85% of all equity short positions going through Goldman's brokerage in March 2010.

If hedge funds that are more exposed to short selling risk are rewarded with larger average returns, there should be a positive cross-sectional relation between hedge funds' exposures to short selling risk and their performance. My study is the first to address this possibility empirically.

## 3. **Data and variable measurement**

### *3.1. Hedge fund data*

I obtain hedge fund data from the Lipper TASS database. Since my main measure of short selling risk begins in 1996, when the OptionMetrics data become available, my sample period of hedge funds is from January 1996 through December 2015. TASS classifies hedge funds into 11 self-reported style categories: convertible arbitrage, dedicated short bias, emerging markets, event driven, equity market neutral, fixed income arbitrage, funds of funds, global macro, long/short equity hedge, managed futures, and multi strategy. Since this study focuses on shorting-selling risk in U.S. equity markets, I only include U.S. equity-oriented hedge funds and drop global macro, emerging markets, fixed income arbitrage, and managed futures.

Following prior research, I apply several screens to the TASS hedge fund data. First, to address the concern that hedge funds may backfill returns when newly added to the database, I exclude the first 12 months of returns for each fund. Second, I only include funds that report monthly net-of-fee returns in U.S. dollars and allow for redemption at a monthly or higher frequency. Third, I delete duplicate funds from the sample and exclude funds with assets under management (AUM) of less than $5 million. Finally, I require each fund to have at least 24 return observations. My sample then contains 5,568 hedge funds over the period from January 1996 to

December 2015.

[Insert Table 1 about here]

Panel A of Table 1 reports summary statistics of hedge fund excess returns. It shows that the average monthly excess fund return is 0.38% and the standard deviation is 3.45%. Panel A also reports the summary statistics of hedge fund excess returns by investment style. Each fund in the sample is characterized as one of the following investment styles: convertible arbitrage, dedicated short bias, event driven, equity market neutral, fund of funds, long/short equity and multi-strategy. The different styles exhibit sufficient cross-sectional variation in average monthly excess return.

Panel B of Table 1 reports the summary statistics of fund characteristics, including fund size, fund age, management fee, incentive fee, high water mark provision, minimum investment amount, lockup period, notice period, payout period, and whether the fund uses leverage. These summary statistics resemble those in the previous studies that use the TASS data on hedge funds.

*3.2. Option data*

I obtain option data from OptionMetrics for the period from 1996 through 2015. Following Blocher and Ringgenberg (2016), I drop options with less than 7 days or greater than 180 days to maturity, offer price greater than ask price, nonpositive implied volatility, bid-ask spreads greater than 25%, and the absolute value of log moneyness greater than 0.3. These filters help to exclude illiquid options. Option bid-ask spread is measured as the difference between the best offer and best bid divided by the midpoint. Moneyness is computed as the closing stock price divided by the strike price of the option. I obtain the risk-free rate from OptionMetrics and linearly interpolate it for days to maturity where no rate is listed. As the underlying stocks of many options pay dividends, I need to consider the present value of the dividend. I only keep options with regular dividends (annually, semiannually, quarterly, and monthly).

*3.3. Measure of short selling risk*

Following Engelberg et al. (2018), I use option implied loan fee as the main measure of short selling risk. Option implied loan fee is the required shorting fee within the option maturity, to eliminate the put-call parity deviations. The option-based measure of short selling risk offers at least two advantages. First, it captures forward-looking shorting costs and thus comports with the theoretical predictions of D'Avolio (2002). Compared to the level of current equity loan fees, short sellers are more concerned with the dynamic risks of short selling: the risk of increases in future loan fees and the risk of recalls. Engelberg et al. (2018) consider this measure as a proxy for ex ante short selling risk. Engelberg et al. (2018) and Muravyev et al. (2018) find that option implied loan fees forecast both future loan fee increases and future recalls. Second, compared to the Markit data which is available only for a few years, use of option-implied loan fee as a proxy allows me to perform the analyses over a long sample period, from January 1996 through December 2015.

Ofek et al. (2004) and Evans et al. (2009) show that, when short selling costs are significantly high, put-call parity diverges from predicted value. We can use option prices to estimate short selling costs associated with a synthetic short position of the underlying stock, which can be established by writing a call option and buying a put option with the same strike price and time to maturity.[8] I estimate option implied loan fees by using the following put-call parity equation.

[8] More recently, several studies have adopted a similar approach to measure short selling fees (e.g., Muravyev et al. 2018; Weitzner 2017).

$$Call_{i,t} - Put_{i,t} = S_{i,t} - K \times e^{-r(T-t)} - \sum_{j=1}^{6} D_{i\,j} \times e^{-r(T-t)} \quad (1)$$

where *Call* is the closing bid of call prices, *Put* is the closing ask of put prices, *S* is closing stock price for stock *i* on date *t*, *K* is the strike price, *Di,j* represents all *j* dividends paid on stock *i* from date *t* until expiration.[9]

The implied loan fee for a short position within the maturity is calculated in three steps. First, I solve for Model (1) to get the interest rate (*r*) that equalizes the put-call parity. Second, I calculate the option implied fee as the difference between the market-forward risk-free interest rate at date *t* with the same maturity and the implied *r* that equalizes the put-call parity. Third, option implied loan fee is computed from each unique put-call-strike-expiration pair. For each stock and month, I measure a firm's option implied (annualized) loan fee as the standard deviation of implied (annualized) loan fee across all pairs.

Similar to Drechsler and Drechsler (2018), I construct an investable short risk factor, which is monthly excess returns of long short (stock) portfolios based on the measure of short selling risk—the option implied loan fees. Specifically, for each month, I form 10 equal-weighted portfolios of stocks sorted by option implied loan fees in the past month and then hold these portfolios for one calendar month. The short risk factor is the return spread between the decile of stocks with low option implied loan fees (bottom decile) and the decile of stocks with high option implied loan fees (top decile). By construction, the return spread captures the risk premium that arbitrageurs demand for bearing short selling risk (in that the portfolio return of high shorting fee stocks, which is significantly lower than that of low fee stocks).

[9] I don't incorporate the early exercise premium for American options. The possible bias created by the early exercise of American options is likely mitigated by using the options that are closer to the money and with lower regular dividends. My results are robust to use only European options to estimate the short selling risk.

Engelberg et al. (2018) use the volatility of daily shorting fees to measure the uncertainty of future loan fees. Thus, I also construct an alternative measure of short risk based on the volatility of option implied loan fees. For each stock and month, I measure a stock's volatility of option implied (annualized) loan fee as the standard deviation of implied (annualized) loan fee across all pairs. The short selling risk factor is the return spread on a long short portfolio that is long the decile of stocks with long volatility of loan fees and short the decile of stocks with high loan fees. The results based on the volatility of option implied loan fee are reported in Table 13.

[Insert Table 2 about here]

Panel A of Table 2 shows that, on average, stocks with high option-implied loan fees earn relatively lower subsequent returns than those with low fees. In particular, the low-fee decile (decile 1) earns a monthly excess return of 1.03% and a monthly Fama-French four factor alpha of 0.31%, and the high-fee decile (decile 10) yields a monthly excess return of -0.51% and a monthly Fama-French four factor alpha of -1.23%. Consequently, the average return and Fama-French four factor alpha of the short risk factor, as shown in Panel B, is 1.54% and 1.59% per month, respectively.

[Insert Figure 1 about here]

Figure 1 depicts the time-series of monthly returns of the short risk factor. There is substantive variation in the risk factor return over time, ranging from a low value of about -0.16% to a high value of around 5.36%. Such time-series variation is valuable for testing the potential impact of short selling risk in determining hedge fund returns.

*3.4. Mean-Variance Spanning Tests*

One natural question to ask is whether the short risk factor captures the risk premium of existing well-known factors. In other words, whether a portfolio of the commonly used factors can replicate the performance of the short risk factor?

In this section, I explore whether the short risk factor lies outside the mean-variance frontier of the common risk factors, which is sufficient to show that the short risk factor cannot be replicated by a portfolio of these factors. Huberman and Kandel (1987) are the first to provide a mean-variance spanning test on the hypothesis of whether *N* assets can be replicated in the mean-variance space by a set of *K* benchmark assets. It has been widely applied in recent studies to test the same hypothesis (e.g., Kan and Zhou (2012), and Han, Zhou, and Zhu (2016)). To do so, I run a regression of the short risk factor on a portfolio of well-known factors the FF3 factors, FF5 factors, or HXZ factors:

$$SR_t = a_0 + \sum \beta_i \, rf_{i,t} + e_t \tag{2}$$

where $SR_t$ the monthly return on the short risk factor and $rf_{i,t}$ represents the monthly return on factor *i* in each replicating portfolio.

The spanning hypothesis is equivalent to the following parametric restrictions on the model:

$$H_0 : a_0 = 0, \sum \beta_i = 1 \tag{3}$$

Following prior studies, I run six spanning tests: (1) Wald test under conditional homoskedasticity, (2) Wald test under independent and identically distributed (IID) elliptical distribution, (3) Wald test under conditional heteroskedasticity, (4) Bekerart-Urias spanning test with errors-in-variables (EIV) adjustment, (5) Bekerart-Urias spanning test without the EIV adjustment, and (6) DeSantis spanning test. All six tests have asymptotic chi-squared distribution with 2N (N=1) degrees of freedom.

[Insert Table 3 about here]

Table 3 presents the spanning test results for the FF3+LIQ factors, FF3+LIQ+UMD factors, FF5 factors, and HXZ factors. For each factor model, all six tests reject the null hypothesis that the short risk factor is inside the mean-variance frontier of the factors. In other words, the results suggest that the INFO factor expands the frontier relative to these other well-known factors and it cannot be replicated by these factors.

*3.5. Hedge fund standard risk factors*

To measure risk-adjusted performance, I control for commonly used risk factors identified in the hedge fund literature. First, I control for the Fung and Hsieh (2004) seven factors: an equity market factor (*MKT*); a small-minus-big size factor (*SMB*); change in the constant maturity yield of the 10-year Treasury; change in the yield spread between Moody's Baa bond ($\Delta$*TERM*) and the 10-year Treasury bond ($\Delta$*CREDIT*); and trend-following factors for bonds (*PTFSBD*), currency (PTFSFX), and commodities (PTFSCOM), respectively. These factors have been shown to explain the cross-sectional variation of hedge fund returns (e.g., Fung, Hsieh, Naik, and Ramadorai 2008; Sadka 2010). Second, I include the Carhart (1997) momentum factor, as momentum is one of most common strategies implemented by equity funds, and the Pastor and Stambaugh (2003) liquidity factor to control for liquidity risk, as Aragon (2007) and Sadka (2010) show that liquidity risk exposure is an important determinant of hedge fund performance. In untabulated analysis, I find that the short risk factor does not significantly co-vary with any of the other factors. The factors that are most correlated with the short risk factor are market (MKT) and size (SMB). The correlations are -0.24 and -0.25, respectively.

## 4. Empirical analysis

### *4.1. Portfolio Sorts*

To test the hypothesis in Section 2, I start with the portfolio sorting approach. Starting with February 1999, I form 10 equal-weighted hedge fund portfolios sorted on the basis of their short risk exposures for each month. Each fund's short risk exposure is estimated by regressing the fund's excess returns on the short risk factor and other standard risk factors over a 36-month rolling window. I require that funds have at least 24 return observations during the 36-month rolling window. I estimate the following regression.

$$Ret_{i,t} = a_0 + a_1\, SR_t + a_2\, MKT_t + a_3\, LIQUIDITY_t + a_4\, SMB_t + a_5\, UMD_t + a_6\, PTFSBD_t + a_7\, PTFSFX_t + a_8\, PTFSCOM_t + a_9\, \Delta TERM_t + a_{10}\, \Delta CREDIT_t + e_{i,t}, \quad (4)$$

where $Ret_{i,t}$ is the return of fund $i$ in month $t$ and $SR$ is the short risk factor in month $t$, which is defined in section 3.4. $a_1$ captures fund i's short risk exposure. In addition, I control for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

I examine the performance of hedge fund short-risk-exposure deciles over the next month after portfolio formation. Besides excess returns of hedge funds, I measure alphas by regressing the time series of the excess returns of each decile portfolio on the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

[Insert Table 4 about here]

Table 4 reports the results for hedge fund performance across the short-risk-exposure deciles. The portfolio sorts show a monotonic and positive relation between hedge funds' short risk exposures and next-month average returns. The portfolio with the highest short risk exposure (decile 10) delivers an excess return of 0.66% per month and an alpha of 0.43% per month, while the portfolio with the lowest short risk exposure (decile 1) shows an excess return of 0.22% per month and an alpha of -0.02% per month. The return spread between the two extreme portfolios is 0.44% per month with a *t*-statistic of 2.68, and the spread in alpha between the two portfolios is 0.45% per month with *t*-statistic of 2.78. Thus, the results from portfolio sorts support the notion that short risk exposure explains the cross section of hedge fund returns, even after adjusting for standard risk factors.

[Insert Figure 2 about here]

Figure 2 plots the cumulative returns to a long-short strategy for the two extreme portfolios over the period from February 1999 to December 2015. The long-short portfolios earn large returns: yielding a cumulative excess return of 134% from February 1999 through December 2015. Thus Figure 2 shows a strong relation between hedge funds' short risk exposures and future returns.

*4.2. Cross-Sectional Regressions*

In this section, I run Fama-MacBeth (1973) regressions of fund excess returns on short risk exposure, controlling for a set of fund characteristics and fund style dummies. Specifically, I estimate the following regression.

$$Ret_{i,t+1} / Alpha_{i,t+1} = a_0 + a_1\, SR\ exposure_{i,t} + a_2\, Size_{i,t} + a_3\, Age_{i,t} + a_4\, Flow[-12, -1]_{i,t} + a_5\, Return[-12, -1]_{i,t} + a_6\, Mgmt\ fee_{i,t} + a_7\, Incentive\ fee_{i,t} + a_8\, High\ water\ mark_{i,t} + a_9\, Min\ investment_{i,t} + a_{10}\, Lockup_{i,t} + a_{11}\, Notice_{i,t} + a_{12}\, Payout_{i,t} + a_{13}\, Leverage_{i,t} + Fund\ style\ dummies + e_{i,t+1} \tag{5}$$

where the dependent variable is one-month-ahead excess return or the estimate of one-month-ahead fund alpha. $SR\ exposure_{i,t}$ is fund *i*'s short risk exposure estimated from regression model (4), using fund returns in the past 36-month rolling window up to month *t*. The set of fund characteristics include fund size, *Size*; fund age, *Age*; fund flow, *Flow[-12, -1]*; fund return, *Return[-12, -1]*; management fee, *Mgmt fee*; incentive fee, *Incentive fee*; the high-water mark provision, *High water mark*; minimum investment, *Min investment*; lockup period, *Lockup*; redemption notice period, *Notice*; payout period, *Payout*; leverage, *Leverage*; and fund style dummies. The t-statistics are based on Newey-West (1987) standard errors with four lags.[10]

*Size* is the natural logarithm of monthly AUM (in billions of dollars). *Age* is the natural logarithm of the number of months since fund's inception. *Flow[-12, -1]* is the net fund flows over the previous 12 months. *Return[-12, -1]* is the average fund excess return over the previous 12 months. *Mgmt fee* is a fixed fee as a percentage of AUM. *Incentive fee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate. *High water mark* is an indicator variable that equals one if a high-water mark provision is used and 0 otherwise. *Min investment* is the natural logarithm of the minimum initial investment amount (in millions of dollars) that the fund requires from its investors. *Lockup* is the natural logarithm of the minimum number of days that the investor has to wait before she can withdraw her investment. *Notice* is the natural logarithm of the minimum number of days an investor needs to notify the fund before redeeming her investment from the fund. *Payout* is the natural logarithm of the number of days before investors receive cash back once sell orders are processed. *Leverage* is an indicator variable that equals one if leverage is used and 0 otherwise.

[Insert Table 5 about here]

Table 5 reports the results from the cross-sectional regressions. First, the univariate regressions show that, with either fund excess return or alpha as the dependent variable, the

[10] As suggested by Greene (2002), I set the lag length = $T^{1/4} = 239^{1/4} \approx 4$.

coefficient on *SR exposure* is positive and significant. This confirms the results of portfolio sorts in Table 4. In addition, from multivariate regressions controlling for fund characteristics and style dummies, I still find a robust positive relation between short risk exposure and next-month fund returns. Specifically, in column (2), where fund excess return is the dependent variable, the coefficient on *SR exposure* is 0.016 (*t*-statistic = 2.42), and in column (4), where fund alpha is the dependent variable, the coefficient on *SR exposure* is 0.011 (*t*-statistic = 2.95). Lastly, the coefficients on fund characteristics comport with those of previous studies on hedge funds. For example, larger hedge funds as well as those that (1) did well during the past 12 months, (2) charge higher incentives fees, (3) use a high-water mark, and (4) have longer lockup periods tend to perform better.

Taken together, I obtain robust evidence from both portfolio analyses and cross-sectional regressions that short risk exposure can significantly and positively predict cross-sectional hedge fund returns, even after adjusting for standard risk factor exposures and controlling for fund characteristics.

*4.3. Short risk exposure and fund characteristics*

To understand why some funds are more exposed to short selling risk than others, I then explore the relation between hedge funds' short risk exposure and a set of fund characteristics. Specifically, I employ the following Fama–MacBeth (1973) regression.

$$SR\ exposure_{i,t+1} = a_0 + a_1\, Size_{i,t} + a_2\, Age_{i,t} + a_3\, Flow[-12, -1]_{i,t} + a_4\, Ret[-12, -1]_{i,t} + a_5\, Mgmt\ fee_{\,i,t} + a_6\, Incentive\ fee_{i,t} + a_7\, High\ water\ mark_{i,t} + a_8\, Min\ investment_{i,t} + a_9\, Lockup_{i,t} + a_{10}\, Notice_{i,t} + a_{11}\, Payback_{i,t} + a_{12}\, Leverage_{i,t} + Fund\ style\ dummies + e_{i,t+1} \qquad (6)$$

where $SR\ exposure_{i,t+1}$ is fund $i$'s short risk exposure for month $t+1$, which is estimated from Model (4) using past 36-month rolling estimation window. Regarding to fund characteristics, following prior studies (e.g., Agarwal, Daniel, and Naik 2009; Jiang and Kelly 2014), I include fund size, fund age, fund flow, past return, management fee, incentive fee, high water mark, minimum investment amount, lockup period, redemption notice period, payback period, and leverage. Finally, I include investment style dummies to control for unobserved heterogeneity across styles. Test statistics are based on Newey-West (1987) standard errors with four lags.

[Insert Table 6 about here]

Table 6 presents the results. Columns 1 reports results without including fund style dummies, while column 2 reports results controlling for fund style. First, I find that the high short-risk-exposure funds are those that charge higher incentive fees and have a high water mark provision, consistent with the notion that greater managerial incentives lead to more risk taking (e.g., Agarwal, Daniel, and Naik 2009). For example, with a high water mark provision, a manager earns incentive fees when the NAV exceeds the highest historical level of the fund. This could incentivize a fund manager to take more risks to earn more fees. Second, hedge funds that employ share restrictions—that is, those that have longer lockup and payback periods—are more susceptible to short selling risk. Hedge funds that bet against overpricing are likely to face a greater risk of fund outflow if prices of overpriced securities move further away from the fundamental values. Restrictions on redemptions could shield funds from outflows and forced liquidations and thus enable funds to have more flexibility to take short positions. Lastly, hedge funds that employ leverage have larger short risk exposures, consistent with the idea that hedge funds often use leverage to exploit mispricing opportunities. Taken together, these results are consistent with the notion that high short-risk-exposure funds take more risk and earn higher returns, while low short-risk-exposure funds take less risk and earn lower returns.

*4.4. Style analysis*

In this section, I analyze the effect of short risk exposure in explaining the variation in hedge fund returns for each different investment styles. Given the diversity of hedge funds' investment strategies and the fact that not every fund uses short selling, I expect to observe cross-sectional heterogeneities in funds' short risk exposures across different investment styles. There are several fund styles that only a few funds follow, in which case I may lack the power to detect evidence of a significant influence of short risk exposure. For example, monthly decile portfolios of funds in convertible arbitrage, dedicated short bias, and equity market neutral contain below 10 funds on average. Thus, following Agarwal et al. (2009), I further classify hedge funds into four groups according to their investment strategy: directional arbitrage (i.e., long/short equity and dedicated short bias funds), nondirectional arbitrage (i.e., convertible arbitrage, event driven, and equity market neutral funds), multi-strategy, and funds of funds.

[Insert Table 7 about here]

Table 7 presents the results. For funds in each investment group, I sort funds in each investment group into deciles based on their short risk exposures and evaluate the next-month equal-weighted fund return of each decile. First, I observe that directional funds have a larger variation in short risk exposures than other types of funds. Second, I find that short risk exposure relates positively and significantly to hedge fund returns only for directional funds but not for other types of funds. Specifically, for directional hedge funds, the return spread between the top and bottom short-risk-exposure deciles is 0.67% per month, with a *t*-statistic of 2.99, and the spread in alpha is 0.67% per month, with *t*-statistic of 2.89. These findings are consistent with the idea that, unlike other types of funds, some directional funds aim to profit from arbitrage opportunities by short selling, which is risky and generates higher returns to arbitrageurs.

*4.5. Long-term holding horizons*

In this section, I extend the baseline analysis of monthly short-risk-exposure deciles by holding them for longer horizons. Table 8 reports the average monthly returns of deciles of hedge funds sorted on the basis of their short risk exposures over various holding horizons, ranging from three months to 12 months after portfolio formation.

[Insert Table 7 about here]

I find the average monthly excess returns and alphas both decline with the length of holding period. Over the next 3 (6) months, the hedge funds belonging to the top short-risk-exposure decile on average outperform those from the bottom decile by 0.06% (0.12%) per month on a risk-adjusted basis. At the 9-month horizon, the difference in alpha shrinks to 0.24%, which is no longer statistically significant. The results in Table 8 are consistent with the time variation in hedge funds' short risk exposures, which could result from the dynamic nature of hedge fund trading strategies.

[Insert Table 9 about here]

In addition, in each month, I sort hedge funds into deciles on the basis of their short risk exposures and then track average fractions of funds that stay in the initial decile or migrate to other deciles in the next three or nine months. Table 9 presents the transition matrix for hedge fund portfolios sorted on short risk exposure. Panel A (B) shows that about 65% (41%) of the hedge funds currently ranked in the top decile by short risk exposure remain in the top decile after 6 (12) months, lending further support for the time-varying nature of hedge funds' short risk exposures.

*4.6. Short risk exposure and hedge fund skills*

An alternative explanation of the outperformance of high short-risk-exposure funds is that managers of those funds have superior skill. To investigate this possibility, I consider two types of hedge fund skills documented in the literature. First, some managers may be better than others at stock picking. In particular, some managers may be able to identify temporarily overpriced stocks (e.g., Jank and Smajlbegovic 2016; Choi et al. 2017). I use the extent to which hedge funds are exposed to systematic risk factors, proposed by Titman and Tiu (2011), as a proxy for stock picking skill. Consistent the idea that funds with skilled managers tend to outperform, Titman and Tiu (2011) show that funds less exposed to systematic risk (i.e., a low $R^2$ when regressing fund returns on the Fung and Hsieh (2004) seven factors) are associated with higher Sharpe ratios, higher information ratios, and higher alphas.

Some managers may also be better able to time the market. Studies show that arbitrage profitability varies with future market conditions, such as return, liquidity, and volatility (e.g., Cooper, Gutierrez, and Hameed 2004; Chordia, Subrahmanyam, and Tong 2014; Daniel and Moskowitz 2016; Moreira and Muri 2017). If fund managers can forecast market conditions, they can adjust their short positions accordingly to gain a larger profit from short selling. Consistent with this idea, Moreira and Muri (2017) show that volatility timing generates large alphas and increases Sharpe ratios for anomaly-based trading strategies, such as size, value, momentum, and profitability. I focus on three types of documented market-timing skills, namely timing with respect to market return, volatility, and liquidity. Following prior studies (Chen and Liang 2007; Cao et al. 2013) and based on the model of Henriksson and Merton (1981), for each individual fund, I estimate the following regression.

$$Ret_{i,t} = a_0 + a_1\, MKT_t + a_2\, MKT_t \times I\,\{StateHigh_t\} + a_3\, LIQUIDITY_t + a_4\, SMB_t + a_5\, UMD_t + a_6\, PTFSBD_t + a_7\, PTFSFX_t + a_8\, PTFSCOM_t + a_9\, \Delta TERM_t + a_{10} \Delta CREDIT_t + e_{i,t}, \quad (7)$$

where $Ret_{i,t}$ is the excess return of fund *i* in month *t*; $MKT_t$ is the market factor; $I\,\{StateHigh_t\}$ is a dummy variable that equals one when the market state variable in month *t* is greater than its time series mean and zero otherwise, where the market state variable is return, volatility, or liquidity. The coefficient $a_2$ measures market timing abilities. For market return or liquidity, a significantly positive $a_2$ suggests that fund managers can predict return or liquidity. That is, their hedge funds tend to increase their loading on the market factor when the market return or aggregated liquidity is high. For market volatility, a significantly negative $a_2$ suggests an ability to predict volatility. That is, hedge funds will decrease their loading on the market factor when the volatility is high. Similar to Model (4), I control for the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor.

[Insert Table 10 about here]

First, to explore whether managers of hedge funds with larger short risk exposure exhibit superior skills, I examine the average hedge fund skills within each decile of short risk exposure. Table 10 reports the results. I find that managers of hedge funds with larger short risk exposure are relatively better at stock picking than those of funds with smaller exposures. Specifically, the average $R^2$ is 0.46 for the hedge funds in top decile of short risk exposure, while the hedge funds in bottom decile of short risk exposure have an average $R^2$ of 0.54. The difference in average $R^2$ between the two deciles is 0.08 with a t-statistics of 4.69. However, I find no evidence that hedge funds in the top decile of short risk exposure have better timing abilities. Across all three measures of market timing, none of them exhibits a significantly difference for hedge funds between the top and bottom deciles of short risk exposure.

[Insert Table 11 about here]

Next, to understand whether the outperformance of high short-risk-exposure funds is subsumed by their stock picking skills, I perform double sorts by first sorting into quintiles based on Titman and Tiu (2011)'s $R^2$ and then sorting into quintiles based on short risk exposure. Table

11 presents the results. Across quintiles of $R^2$, the return spreads between the top and bottom short-risk-exposure quintiles are both statistically and economically significant, ranging from 0.44% to 0.38% per month. On a risk-adjusted basis, the spreads in alphas are similar in magnitude, ranging from 0.49% to 0.35% per month.[11] These results indicate that a significant component of hedge fund returns to short risk exposure is indeed the risk premium for bearing short selling risk, even after controlling for skill variables.

*4.8. Short risk exposure and mutual fund performance*

In this section, I use mutual funds as a comparison group to provide further evidence on my research question. Hedge funds and mutual funds both are managed portfolios. Mutual funds typically employ a buy-and-hold strategy on a class of assets stipulated in their prospectuses. Unlike their hedge fund counterparts, many of them do not short. For example, as documented by Brown, Carlson, and Chapman (2000), only about 30 percent of mutual funds are allowed to use shot selling by their charters and only 2 percent actually do sell short. Therefore, I do not expect mutual funds to be significantly exposed to short selling risk. As a result, this risk cannot explain their returns in the cross-section.

By using monthly returns of individual mutual funds from the CRSP mutual fund database, I examine whether mutual funds' exposure to short selling risk predicts their performance for the sample period from January 1996 to December 2015. Following prior studies (e.g., Dong, Feng, and Sadka 2016), I exclude the first 12-month fund returns to mitigate the incubation bias in the CRSP mutual fund data. I also exclude money-market funds and index funds. Similar to my main analyses in Section 4.1, I first estimate monthly short risk exposure for each mutual fund from the

[11] In untabulated analysis, I also perform double sorts, first on each of three measures of timing abilities and then on short risk exposure, and obtain similar findings.

time series regressions of mutual fund excess returns on the short risk factor over a 36-month rolling window. I then form decile portfolios by sorting mutual funds based on their short risk exposures.

[Insert Table 12 about here]

Table 12 presents the results. First, I find that, compared to hedge funds, mutual funds on average have smaller short risk exposures and exhibit smaller cross-sectional variation in short risk exposure. For example, the difference of short risk exposure between the top and bottom deciles is 0.32, which is less than half of the difference for hedge funds. In addition, as expected, the portfolio sorts show no monotonic, positive relation between short risk exposure and next-month average fund returns. For example, the portfolio with the highest short risk exposure (i.e., decile 10) delivers an excess return of 0.27% per month and an alpha of -0.06% per month. Meanwhile, the decile portfolio with the lowest short risk exposure (i.e., decile 1) shows an excess return of 0.38% per month and an alpha of -0.011% per month. The performance difference between the two portfolios is insignificant: the return spread is 0.11% (*t*-statistic = 0.81) per month and the spread in alpha is -0.05% (*t*-statistic = -0.29) per month. These results confirm that the superior performance of high short-risk-exposure hedge funds manifests compensation for bearing short selling risk. These results also imply that one possible explanation for the alphas of hedge funds, compared to mutual funds, is that the former use short sell, which is risky but generates large arbitrage profits.

## 5. Additional analysis

### *5.1 Alternative measures of short selling risk*

[Insert Table 13 about here]

My first robustness check explores an alternative measure of short selling risk. As discussed in section 3.3, I consider the variance of option implied fee as an alternative measure of short selling risk, because the variation in option implied fees tells us about variation in future lending fees. Panel A of Table 13 presents the results. The portfolio sorts formed on this measure of short selling risk—the variance of option implied fee—reveal a significantly positive relation between a fund's risk exposure and next month's returns in the cross-section. For example, the top short risk exposure hedge funds, on average, outperform the bottom risk exposure hedge funds by 0.41% (*t*-statistic = 2.77) on a risk-adjusted basis.

### *5.2. Alternative performance evaluation model*

In my main analysis, I estimate alphas for short-risk-exposure deciles using a nine-factor benchmark model, including the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. In this section, I use the Fama-French five-factor model, including market, size, value, profitability and investment factors, as an alternative benchmark model. Panel B of Table 13 shows that spreads in alpha between the top and bottom short exposure deciles is 0.49 (t-statistics = 2.91), which remains economically large and statistically significant.

### *5.3. Value-weighted fund returns*

Last, instead the equal-weighted portfolio returns in the baseline analysis, I use the value-weighted portfolio returns weighted by funds' monthly assets under management (AUM) as a robustness check. Again, Panel C of Table 13 shows that the spread in alpha between the two deciles is 0.24% ($t$-statistic = 2.03) per month, suggesting that my main findings are robust to using value-weighted portfolio returns.

## 6. Conclusion

I examine whether short selling risk, a type of arbitraging risk that affects the short side of arbitrage, contributes to hedge fund returns. As suggested by theories, arbitrageurs should be compensated for the risks they take. As a result, hedge funds that are largely exposed to short selling risk when betting against overpriced stocks face larger risks and should be rewarded with larger arbitrage profits. Using a comprehensive sample of U.S. equity-oriented hedge funds from January 1996 to December 2015, I find a significant and positive relation between hedge funds' short risk exposures and cross-sectional future fund returns. Funds that in the top decile sorted by short risk exposure, on average, outperform those in the bottom decile by 0.45% over the next month on a risk-adjusted basis. Results from Fama-MacBeth (1973) regressions also confirm this positive relation after controlling for various fund characteristics and styles. Further tests show that a considerable component of the explanatory power of short risk exposure arises from compensation for bearing short selling risk, even after controlling for fund skills.

My study contributes to the understanding of the superior performance of hedge funds. Identifying funds with superior performance matters to investors, who allocate money among different investments. However, the success of hedge fund performance evaluation depends on the appropriateness of the benchmark model used. It has been well documented that hedge funds often use trading strategies that are not available to other managed portfolios and thus bear unique risks that are not captured by standard benchmark models. In particular, many hedge funds use short selling. This study is the first to show that the exposure to short selling risk relates positively to hedge fund returns. The evidence here highlights the importance of accounting for short selling risk when evaluating hedge fund performance. In addition, I find no such result for mutual funds, whose investments are primarily on the long side. This suggests that one possible reason for the outperformance of hedge funds, relative to mutual funds, is that the former use short selling to bet against mispricing—a risky strategy but one that can generate large arbitrage profits.

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**Figure 1 Short Risk Factor Monthly Returns**

This figure plots the time series of the short risk factor returns from January 1996 to December 2015. Short selling risk is measured as the option implied loan fees. For each month, I form equal-weighted decile portfolios of stocks sorted by option implied loan fees and then hold these portfolios for one calendar month. The short risk factor is the return spread between the decile of stocks with low option-implied shorting fees (decile 1) and the decile of stocks with high fees (decile 10).

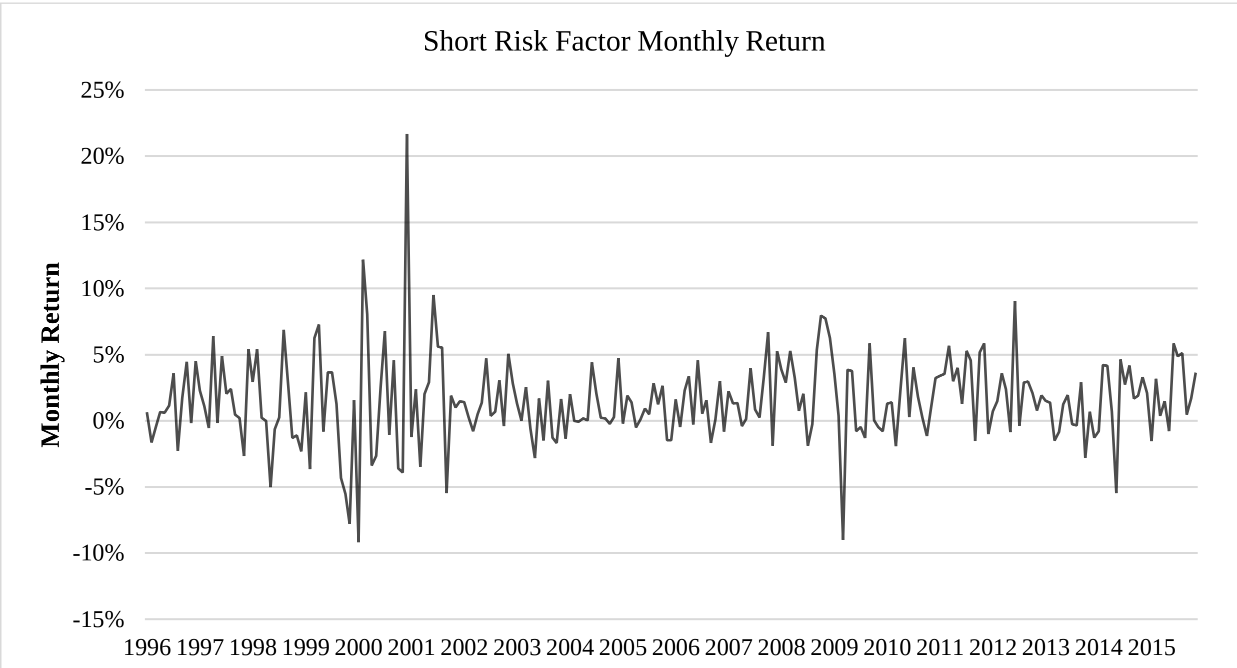

**Figure 2 Cumulative Portfolio Returns over Time**

This figure plots the cumulative returns to a long-short portfolio that longs hedge funds in the top decile of short risk exposure and shorts hedge funds in the bottom decile of short risk exposure. These equal-weighted portfolios are then held for one calendar month. Starting from February 1999, for each month, I form the deciles based on hedge funds' short risk exposure estimated from the past 36 months and track their returns over the next month.

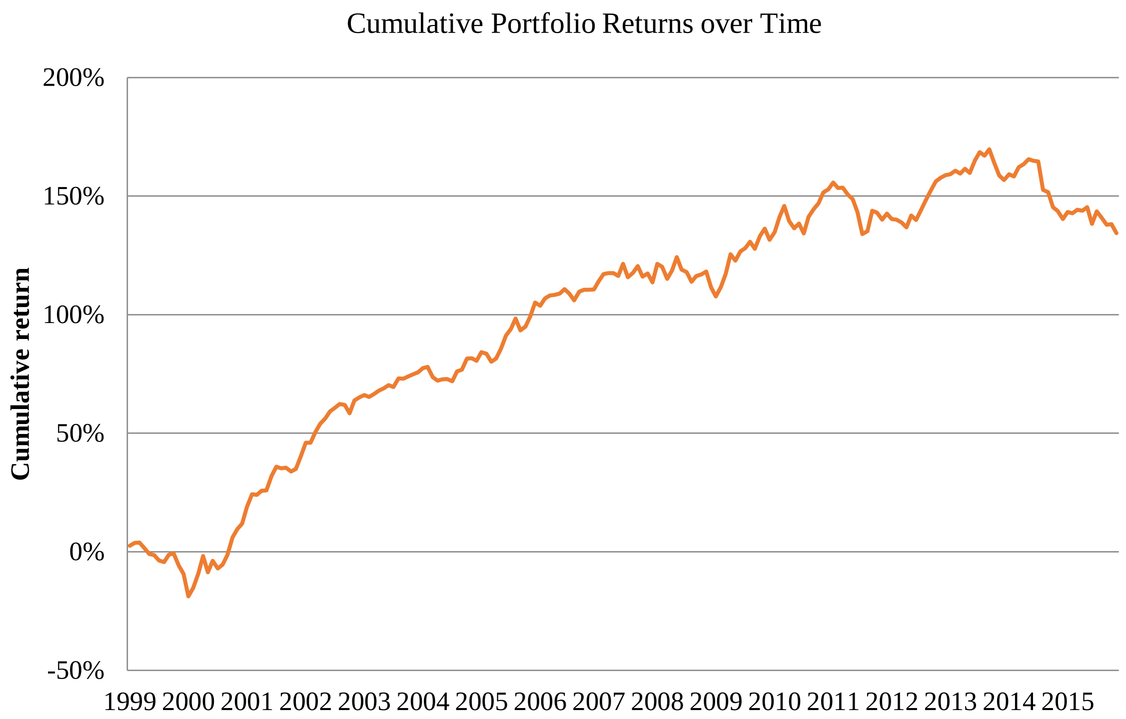

**Table 1 Descriptive Statistics**

This table presents the descriptive statistics for monthly hedge fund returns and fund characteristics over the sample period from January 1996 to December 2015. The sample includes U.S. equity-oriented hedge funds that report monthly net-of-fee returns in U.S. dollars and have assets under management (AUM) of at least $5 million. Panel A shows the summary statistics of monthly excess returns of hedge funds in each style category and all hedge funds in my sample. Returns are in percent per month in excess of the one-month T-bill rate. *# of funds* is the number of distinct hedge funds in each category. Panel B reports the summary statistics of fund characteristics. *AUM* is assets under management (in millions of dollars). *Age* is the number of months since fund's inception. *Mgmt fee* is a fixed fee as a percentage of AUM. *Incentive fee* is a fixed percentage fee of the fund's net annual profits above a pre-specified hurdle rate. *High water mark* is an indicator variable that equals one if a high-water mark provision is used and 0 otherwise. *Min investment* is the minimum initial investment amount (in millions of dollars) that the fund requires from its investors. *Lockup* is the minimum number of days that the investor must wait before she can withdraw her investment. *Notice* is the minimum number of days an investor needs to notify the fund before redeeming the invested amount from the fund. *Payout* is the number of days before investors receive cash back once sell orders are processed. *Leverage* is indicator variable that equals one if leverage is used and 0 otherwise.

| | # of funds | Mean | STD | P10 | P25 | Median | P75 | P90 |
|---|---|---|---|---|---|---|---|---|
| Panel A: Monthly Excess Hedge Fund Returns (%) | | | | | | | | |
| Convertible arbitrage | 201 | 0.31 | 2.71 | -1.98 | -0.42 | 0.41 | 1.22 | 2.43 |
| Dedicated short bias | 37 | -0.07 | 5.78 | -7.45 | -3.82 | -0.13 | 3.04 | 7.97 |
| Event driven | 590 | 0.49 | 2.86 | -2.18 | -0.40 | 0.50 | 1.54 | 3.17 |
| Equity market neutral | 337 | 0.29 | 2.32 | -2.01 | -0.66 | 0.26 | 1.29 | 2.69 |
| Fund of funds | 2,017 | 0.19 | 2.61 | -2.44 | -0.74 | 0.38 | 1.34 | 2.50 |
| Long/short equity | 1,943 | 0.54 | 4.39 | -4.49 | -1.48 | 0.54 | 2.62 | 5.57 |
| Multi-strategy | 443 | 0.42 | 3.20 | -2.75 | -0.66 | 0.49 | 1.63 | 3.47 |
| All | 5,568 | 0.38 | 3.45 | -3.14 | -0.90 | 0.43 | 1.71 | 3.77 |
| Panel B: Hedge Fund Characteristics | | | | | | | | |
| AUM ($billions) | 5,568 | 163.54 | 322.99 | 9.80 | 20.00 | 51.83 | 148.00 | 401.27 |
| Age (months) | 5,568 | 130.51 | 68.59 | 49.00 | 77.00 | 122.00 | 172.00 | 226.00 |
| Mngt fee (%) | 5,568 | 1.35 | 0.49 | 1.00 | 1.00 | 1.50 | 1.50 | 2.00 |
| Incentive fee (%) | 5,568 | 14.81 | 7.57 | 0.00 | 10.00 | 20.00 | 20.00 | 20.00 |
| High water mark | 5,568 | 0.67 | 0.47 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |
| Min investment ($billions) | 5,568 | 0.91 | 1.45 | 0.05 | 0.10 | 0.50 | 1.00 | 1.00 |
| Lockup | 5,568 | 4.04 | 6.50 | 0.00 | 0.00 | 0.00 | 12.00 | 12.00 |
| Notice | 5,568 | 43.76 | 27.28 | 7.00 | 30.00 | 35.00 | 60.00 | 90.00 |
| Payout | 5,568 | 18.90 | 21.82 | 0.00 | 0.00 | 15.00 | 30.00 | 30.00 |
| Leverage | 5,568 | 0.55 | 0.50 | 0.00 | 0.00 | 1.00 | 1.00 | 1.00 |

**Table 2 Summary Statistics of Short Risk Factor**

This table shows short selling risk, measured by option implied loan fees, is calculated as follows.

$$Call_{i,t} - Put_{i,t} = S_{i,t} - K \times e^{-r(T-t)} - \sum_{j=1}^{6} D_{i\,j} \times e^{-r(T-t)}$$

where *Call* is the closing midpoint of call prices, *Put* is the closing midpoint of put prices, *S* is closing stock price for stock *i* on date *t*, *K* is the strike price, *Di,j* represents all *j* dividends paid on stock *i* from date *t* until expiration. The implied loan fee for a short position within the maturity is calculated by three steps. First, I solve for the above equation to get the interest rate (*r*) that equalizes the put-call parity. Second, I calculate the option implied fee as the difference between the market forward risk-free interest rate at date t with the same maturity and the implied r that equalizes the put-call parity. Third, option implied loan fee is computed from each unique put-call-strike-expiration pair. For each stock and date, I measure a firm's daily option implied (annualized) loan fee is as the average implied (annualized) loan fee across all pairs. Panel A reports monthly returns of 10 equal-weighted decile portfolios of stocks sorted on their option implied loan fees. At the end of each month from February 1996 to December 2015, I sort stocks into deciles by their option implied loan fees. For each decile portfolio, alpha is estimated based on the monthly time series of the portfolio returns, relative to the Fama-French four factors. Both monthly excess return and alpha are reported in percentages. Panel B further presents summary statistics for the short risk factor, which is the return spread between the decile of stocks with low option implied loan fees (decile 1) and the decile of stocks with high fees (decile 10). Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: Portfolio Return by Option Implied Loan Fee Decile

| Portfolio | *Option Implied Loan Fee (bps)* | *Excess Return* | *FF4 Alpha* |
|---|---|---|---|
| 1 (Lowest fee) | -155 | 1.03 | 0.33 |
| | | (3.10) | (3.12) |
| 2 | -50 | 0.90 | 0.21 |
| | | (3.23) | (2.12) |
| 3 | -6 | 0.77 | 0.16 |
| | | (3.08) | (1.68) |
| 4 | 21 | 0.75 | 0.14 |
| | | (3.01) | (1.58) |
| 5 | 41 | 0.72 | 0.07 |
| | | (2.95) | (0.81) |
| 6 | 60 | 0.57 | -0.09 |
| | | (2.49) | (-0.97) |
| 7 | 82 | 0.70 | 0.02 |
| | | (2.73) | (0.24) |
| 8 | 112 | 0.52 | -0.17 |
| | | (2.23) | (-1.81) |
| 9 | 170 | 0.40 | -0.40 |
| | | (1.83) | (-3.17) |
| 10 (Highest fee) | 641 | -0.51 | -1.26 |
| | | (-1.99) | (-6.15) |
| Spread (Low - High) | | 1.54*** | 1.59*** |
| (t-stat) | | (5.18) | (5.57) |

Panel B: Summary Statistics for the Short Risk Factor

| No. Obs. | Mean | Median | 10th percentile | 90th percentile | Standard Deviation |
|---|---|---|---|---|---|
| 239 | 1.54 | 1.34 | -1.65 | 5.38 | 3.33 |

**Table 3 Mean-Variance Spanning Tests of Short Risk Factor**

The table reports the results of tests examining whether the short risk factor can be spanned by the factors of the FF3 model, the FF5 model, or the HXZ model. W is the Wald test under conditional homoskedasticity, We is the Wald test under the IID elliptical, Wa is the Wald test under the conditional heteroskedasticity, J1 is the Bekaert-Urias test with the Errors-in-Variables (EIV) adjustment, J2 is the Bekaert-Urias test without the EIV adjustment, and J3 is the DeSantis test. All six tests have an asymptotic chi-squared distribution with 2N(N=1) degrees of freedom. p-values are shown below the test statistics in parentheses. The sample period is from February 1996 through December 2015.

| Factors | W | We | Wa | J1 | J2 | J3 |
|---|---|---|---|---|---|---|
| FF three factor | 34.47 | 32.18 | 33.83 | 39.61 | 38.91 | 39.27 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| FF five factor | 38.12 | 35.08 | 39.56 | 31.72 | 30.22 | 29.96 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| HXZ q factors | 38.79 | 37.81 | 38.03 | 32.34 | 33.50 | 32.52 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

**Table 4 Short Risk Exposure and Hedge Fund Returns: Portfolio Sorts**

This table reports monthly returns of 10 equal-weighted portfolios of hedge funds sorted on short risk exposure (SR exposure).

$$Ret_{i,t} = a_0 + a_1 SR_t + a_2 MKT_t + a_3 LIQUIDITY_t + a_4 SMB_t + a_5 UMD_t + a_6 PTFSBD_t + a_7 PTFSFX_t + a_8 PTFSCOM_t + a_9 \Delta TERM_t + a_{10} \Delta CREDIT_t + e_{i,t}$$

In each month for each hedge fund with at least 24 returns observations in the past 36 months, short risk exposure (SR exposure) is estimated by regressing the fund excess returns on the short risk factor (*SR*), controlling for the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Based on the funds' SR exposures, I form 10 equal-weighted portfolios. For each portfolio, alpha is estimated based on the monthly time series of the portfolio returns, relative to the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Both monthly excess return and alpha are reported in percentages. Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| Portfolio | *SR Exposure* | *Excess Return* | *Alpha* |
|---|---|---|---|
| 1 (Low SR Exposure) | -0.43 | 0.22 | -0.02 |
| | | (1.14) | (-0.20) |
| 2 | -0.20 | 0.29 | 0.10 |
| | | (2.06) | (1.42) |
| 3 | -0.11 | 0.22 | 0.06 |
| | | (1.81) | (1.09) |
| 4 | -0.06 | 0.25 | 0.11 |
| | | (2.18) | (1.82) |
| 5 | -0.02 | 0.30 | 0.17 |
| | | (2.64) | (2.83) |
| 6 | 0.01 | 0.34 | 0.22 |
| | | (3.13) | (3.15) |
| 7 | 0.04 | 0.40 | 0.27 |
| | | (3.55) | (3.84) |
| 8 | 0.08 | 0.39 | 0.24 |
| | | (3.16) | (3.06) |
| 9 | 0.14 | 0.44 | 0.27 |
| | | (2.93) | (3.04) |
| 10 (High SR Exposure) | 0.33 | 0.66 | 0.43 |
| | | (3.51) | (3.11) |
| Spread (High-Low) | 0.77 | 0.44** | 0.45** |
| *(t-stat)* | | (2.68) | (2.78) |

**Table 5 Cross-Sectional Regressions of Fund Performance on Short Risk Exposure**

This table reports the results from the Fama-MacBeth (1973) cross-sectional regressions of hedge fund one-month-ahead excess return as well as alpha on short risk exposure (SR exposure), controlling for fund characteristics and style dummies.

$$Ret_{i,t+1}/Alpha_{i,t+1} = a_0 + a_1 SR\ exposure_{i,t} + a_2 Size_{i,t} + a_3 Age_{i,t} + a_4 Flow[-12,-1]_{i,t} + a_5 Ret[-12,-1]_{i,t} + a_6 Mgmt\ fee_{i,t} + a_7 Incentive\ fee_{i,t} + a_8 High\ water\ mark_{i,t} + a_9 Min\ investment_{i,t} + a_{10} Lockup_{i,t} + a_{11} Notice_{i,t} + a_{12} Payout_{i,t} + a_{13} Leverage_{i,t} + Fund\ style\ dummies + e_{i,t+1}$$

In each month and for each hedge fund with at least 24 returns observations in the past 36 months, short risk exposure (SR exposure) is estimated by regressing the fund excess returns on the short risk factor, with controls for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Fund characteristics include fund size, age, flows, return, management fee, incentive fee, high water mark, minimum investment, lockup period, redemption notice period, payout period, and style dummies. Both monthly excess return and alpha are reported in percentages. Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | *Excess Return* | | *Alpha* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *SR exposure* | 0.010** | 0.016** | 0.013** | 0.011*** |
| | (2.23) | (2.42) | (2.38) | (2.95) |
| *Size* | | 0.045*** | | 0.043*** |
| | | (3.14) | | (5.73) |
| *Age* | | 0.116*** | | 0.042 |
| | | (3.04) | | (1.55) |
| *Flow[-12,-1]* | | 0.325* | | 0.262** |
| | | (1.71) | | (2.32) |
| *Ret[-12,-1]* | | 0.136*** | | 0.075*** |
| | | (5.88) | | (7.97) |
| *Mngt fee* | | 0.002 | | 0.022 |
| | | (0.28) | | (1.20) |
| *Incentive fee* | | 0.002 | | 0.522*** |
| | | (0.84) | | (4.17) |
| *High water mark* | | 0.618*** | | 0.045*** |
| | | (3.27) | | (2.46) |
| *Min investment* | | 0.001 | | 0.006 |
| | | (-0.70) | | (1.36) |
| *Lockup* | | 0.007*** | | 0.011** |
| | | (2.95) | | (2.13) |
| *Notice* | | 0.029* | | 0.034** |
| | | (1.68) | | (2.81) |
| *Payout* | | 0.009 | | 0.013** |
| | | (0.98) | | (2.79) |
| *Leverage* | | 0.015 | | 0.021 |
| | | (1.58) | | (1.39) |
| Fund style dummies | Yes | Yes | Yes | Yes |
| Adjusted $R^2$ | 0.069 | 0.145 | 0.038 | 0.075 |

**Table 6 Short Risk Exposure and Fund Characteristics**

This table reports the results from Fama-Macbeth regressions of short risk exposure (SR exposure) on fund characteristics.

$$SR\ exposure_{i,t+1} = a_0 + a_1\, Size_{i,t} + a_2\, Age_{i,t} + a_3\, Flow[-12, -1]_{i,t} + a_4\, Ret[-12, -1]_{i,t} + a_5\, Mgmt\ fee_{i,t} + a_6\, Incentive\ fee_{i,t} + a_7\, High\ water\ mark_{i,t} + a_8\, Min\ investment_{i,t} + a_9\, Lockup_{i,t} + a_{10}\, Notice_{i,t} + a_{11}\, Payback_{i,t} + a_{12}\, Leverage_{i,t} + Fund\ style\ dummies + e_{i,t+1}$$

In each month and for each hedge fund with at least 24 returns observations in the past 36 months, short risk exposure (SR exposure) is estimated by regressing the fund excess returns on the short risk factor, with controls for the Fung and Hsieh (2004) seven-factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Fund characteristics include size, age, flows, return, management fee, incentive fee, high water mark, minimum investment, lockup period, redemption notice period, payout period, leverage, and style dummies. Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | *SR Exposure* | |
|---|---|---|
| | (1) | (2) |
| *Size* | -0.017 | -0.016 |
| | (-0.41) | (-0.34) |
| *Age* | -0.061 | -0.026 |
| | (-0.54) | (-0.23) |
| *Flow[-12,-1]* | 1.77** | 1.25 |
| | (2.13) | (1.56) |
| *Ret[-12,-1]* | 0.201*** | 0.188*** |
| | (2.95) | (2.81) |
| *Mngt fee* | 0.048*** | 0.043*** |
| | (5.85) | (5.26) |
| *Incentive fee* | 0.739*** | 0.583*** |
| | (7.06) | (5.31) |
| *High water mark* | 0.410*** | 0.447*** |
| | (6.21) | (6.29) |
| *Min investment* | 0.010 | 0.010 |
| | (0.29) | (0.33) |
| *Lockup* | 0.632*** | 0.564*** |
| | (8.76) | (7.83) |
| *Notice* | 0.059 | 0.053 |
| | (1.22) | (0.36) |
| *Payout* | 0.102*** | 0.069*** |
| | (4.58) | (3.64) |
| *Leverage* | 0.176*** | 0.156** |
| | (3.16) | (2.79) |
| Fund style dummies | No | Yes |
| Adjusted $R^2$ | 0.088 | 0.111 |

**Table 7 Portfolio Sorts on Short Risk Exposure for Hedge Funds within Different Investment Styles**

For hedge funds in each investment style, I sort hedge funds into deciles based on the short risk exposure (*SR* exposure). In each month and for each hedge fund with at least 24 returns observations in the past 36 months, *SR* exposure is estimated by regressing the fund excess returns on the short risk factor, with controls for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. The directional hedge funds include the funds with the investment style of long/short equity and dedicated short bias. The nondirectional hedge funds include the funds with the investment style of convertible arbitrage, event driven, and equity market neutral. Alpha is estimated relative to the Fung and Hsieh (2004) seven factors, the momentum factor, and the Pastor-Stambaugh liquidity factor. Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | 1 (Low SR Exposure) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High SR Exposure) | Spread (High - Low) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Directional hedge funds* | | | | | | | | | | | |
| *SR Exposure* | -0.57 | -0.32 | -0.21 | -0.14 | -0.07 | -0.01 | 0.04 | 0.10 | 0.19 | 0.39 | 0.96 |
| *Excess Return* | 0.13 | 0.33 | 0.32 | 0.31 | 0.35 | 0.41 | 0.42 | 0.46 | 0.64 | 0.80 | 0.67*** |
| | (0.58) | (1.66) | (1.89) | (1.89) | (2.28) | (2.72) | (2.56) | (2.43) | (3.18) | (3.48) | (2.99) |
| *Alpha* | -0.16 | 0.11 | 0.06 | 0.11 | 0.14 | 0.19 | 0.22 | 0.25 | 0.44 | 0.52 | 0.67*** |
| | (-1.09) | (0.94) | (0.77) | (1.43) | (1.88) | (2.42) | (2.17) | (2.38) | (3.48) | (2.82) | (2.89) |
| *Panel B: Nondirectional hedge funds* | | | | | | | | | | | |
| *SR Exposure* | -0.19 | -0.10 | -0.04 | -0.02 | 0.00 | 0.01 | 0.03 | 0.05 | 0.09 | 0.14 | 0.32 |
| *Excess Return* | 0.18 | 0.16 | 0.25 | 0.21 | 0.26 | 0.29 | 0.30 | 0.31 | 0.33 | 0.32 | 0.14 |
| | (2.83) | (2.98) | (2.86) | (3.16) | (3.30) | (3.78) | (4.14) | (4.49) | (2.90) | (2.34) | (1.41) |
| *Alpha* | -0.02 | 0.05 | 0.10 | 0.09 | 0.12 | 0.17 | 0.16 | 0.18 | 0.20 | 0.18 | 0.19 |
| | (-0.16) | (1.15) | (1.31) | (1.28) | (1.52) | (2.19) | (2.10) | (2.33) | (2.85) | (1.57) | (1.58) |
| *Panel C: Multi-strategy hedge funds* | | | | | | | | | | | |
| *SR Exposure* | -0.16 | -0.07 | -0.04 | -0.02 | 0.00 | 0.01 | 0.03 | 0.05 | 0.09 | 0.20 | 0.36 |
| *Excess Return* | 0.45 | 0.62 | 0.40 | 0.45 | 0.39 | 0.43 | 0.53 | 0.44 | 0.38 | 0.64 | 0.18 |
| | (2.31) | (4.03) | (3.12) | (3.50) | (3.00) | (3.52) | (4.59) | (3.56) | (2.61) | (3.47) | (0.92) |
| *Alpha* | 0.24 | 0.52 | 0.28 | 0.36 | 0.29 | 0.36 | 0.44 | 0.39 | 0.20 | 0.50 | 0.26 |
| | (1.37) | (3.87) | (3.02) | (3.61) | (2.74) | (3.56) | (5.14) | (3.79) | (1.53) | (2.72) | (1.54) |
| *Panel D: Funds of funds* | | | | | | | | | | | |
| *SR Exposure* | -0.15 | -0.07 | -0.04 | -0.02 | -0.01 | 0.01 | 0.02 | 0.04 | 0.07 | 0.16 | 0.31 |
| *Excess Return* | 0.22 | 0.20 | 0.27 | 0.29 | 0.29 | 0.24 | 0.30 | 0.33 | 0.28 | 0.21 | -0.02 |
| | (1.38) | (1.48) | (2.21) | (2.42) | (2.52) | (2.08) | (2.60) | (2.91) | (2.42) | (1.34) | (-0.10) |
| *Alpha* | 0.28 | 0.23 | 0.20 | 0.18 | 0.21 | 0.27 | 0.30 | 0.38 | 0.21 | 0.26 | -0.03 |
| | (2.49) | (3.28) | (3.17) | (3.16) | (3.37) | (4.87) | (4.65) | (5.11) | (2.46) | (1.82) | (-0.17) |

**Table 8 Short Risk Exposure and Hedge Fund Returns: Long-Horizons**

In each month, hedge funds are sorted into 10 equal-weighted portfolios based on the short risk exposure (SR exposure). In each month for each hedge fund with at least 24 returns observations in the past 36 months, SR exposure is estimated by regressing the fund excess returns on the short risk factor, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Portfolios are then held for different holding periods, i.e. three, six, nine, and 12 months. This table also reports the excess return and alpha of the high-minus-low spread portfolio for different holding periods. Alpha is estimated relative to the Fung and Hsieh (2004) seven factors, the momentum factor, and the Pastor and Stambaugh liquidity factor. Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | 1 (Low SR Exposure) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High SR Exposure) | Spread (High - Low) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Three months holding period* | | | | | | | | | | | |
| *Excess* | 0.23 | 0.30 | 0.24 | 0.25 | 0.30 | 0.34 | 0.38 | 0.37 | 0.43 | 0.64 | 0.41** |
| *Return* | (1.22) | (2.05) | (1.89) | (2.02) | (2.33) | (2.60) | (2.83) | (2.57) | (2.54) | (3.06) | (2.48) |
| *Alpha* | 0.01 | 0.13 | 0.08 | 0.12 | 0.17 | 0.20 | 0.24 | 0.22 | 0.25 | 0.40 | 0.39** |
| | (0.06) | (1.86) | (1.53) | (1.94) | (2.56) | (2.79) | (3.33) | (2.81) | (2.94) | (2.84) | (2.30) |
| *Panel B: Six months holding period* | | | | | | | | | | | |
| *Excess* | 0.24 | 0.30 | 0.26 | 0.26 | 0.29 | 0.35 | 0.38 | 0.36 | 0.43 | 0.62 | 0.38** |
| *Return* | (1.20) | (1.99) | (1.93) | (1.99) | (2.18) | (2.52) | (2.62) | (2.35) | (2.47) | (2.95) | (2.23) |
| *Alpha* | 0.03 | 0.14 | 0.10 | 0.13 | 0.15 | 0.21 | 0.23 | 0.20 | 0.25 | 0.36 | 0.33* |
| | (0.30) | (2.03) | (1.79) | (2.02) | (2.30) | (2.62) | (3.00) | (2.39) | (2.78) | (2.60) | (1.92) |
| *Panel C: Nine months holding period* | | | | | | | | | | | |
| *Excess* | 0.28 | 0.31 | 0.28 | 0.28 | 0.29 | 0.34 | 0.37 | 0.35 | 0.40 | 0.53 | 0.25 |
| *Return* | (1.20) | (1.91) | (2.04) | (2.06) | (2.15) | (2.44) | (2.52) | (2.39) | (2.46) | (2.88) | (1.64) |
| *Alpha* | 0.05 | 0.15 | 0.13 | 0.15 | 0.15 | 0.20 | 0.22 | 0.19 | 0.21 | 0.29 | 0.24 |
| | (0.47) | (1.91) | (2.19) | (2.10) | (2.22) | (2.47) | (2.67) | (2.45) | (2.68) | (2.43) | (1.52) |
| *Panel D: 12 months holding period* | | | | | | | | | | | |
| *Excess* | 0.27 | 0.32 | 0.29 | 0.29 | 0.29 | 0.34 | 0.38 | 0.37 | 0.41 | 0.45 | 0.18 |
| *Return* | (1.25) | (1.98) | (2.13) | (2.12) | (2.14) | (2.43) | (2.56) | (2.45) | (2.53) | (2.74) | (1.43) |
| *Alpha* | 0.07 | 0.16 | 0.14 | 0.15 | 0.15 | 0.20 | 0.22 | 0.20 | 0.22 | 0.25 | 0.18 |
| | (0.63) | (1.94) | (2.39) | (2.09) | (2.13) | (2.36) | (2.63) | (2.50) | (2.68) | (2.18) | (1.16) |

**Table 9 Initial and Subsequent Short Risk Exposure Rankings**

This table reports the probability of achieving a subsequent short risk exposure (SR exposure) ranking *j* for hedge fund within an initial ranking *i*. In each month *t*, funds are ranked into decile portfolios based on SR exposure. These initial decile rankings are paired with the funds' subsequent six-month SR exposure rankings in Panel A, and with the funds' subsequent 12-month SR exposure rankings in Panel B. In each month *t* for each hedge fund with at least 24 returns observations in the past 36 months, SR exposure is estimated by regressing the fund excess returns on the short risk factor, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | | Month *t* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 (Low SR Exposure) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High SR Exposure) |
| *Panel A: Fund's subsequent three-month short risk exposure ranking* | | | | | | | | | | | |
| Month *t+3* | 1 (Low SR Exposure) | 69% | 18% | 5% | 2% | 1% | 1% | 1% | 1% | 1% | 1% |
| | 2 | 17% | 43% | 19% | 7% | 4% | 2% | 2% | 2% | 2% | 1% |
| | 3 | 5% | 19% | 34% | 19% | 8% | 5% | 3% | 3% | 2% | 1% |
| | 4 | 2% | 7% | 19% | 31% | 18% | 9% | 6% | 4% | 3% | 1% |
| | 5 | 1% | 4% | 9% | 18% | 29% | 19% | 10% | 6% | 3% | 1% |
| | 6 | 1% | 2% | 5% | 10% | 20% | 29% | 19% | 9% | 4% | 2% |
| | 7 | 1% | 2% | 3% | 6% | 10% | 20% | 30% | 19% | 7% | 2% |
| | 8 | 1% | 2% | 3% | 4% | 6% | 10% | 20% | 33% | 18% | 5% |
| | 9 | 1% | 2% | 2% | 3% | 3% | 5% | 8% | 19% | 41% | 17% |
| | 10 (High SR Exposure) | 1% | 2% | 2% | 2% | 2% | 2% | 3% | 5% | 18% | 65% |
| *Panel B: Fund's subsequent nine-month short risk exposure ranking* | | | | | | | | | | | |
| Month *t+9* | 1 (Low SR Exposure) | 45% | 21% | 10% | 5% | 3% | 3% | 2% | 3% | 4% | 4% |
| | 2 | 19% | 25% | 15% | 9% | 7% | 5% | 5% | 5% | 6% | 5% |
| | 3 | 9% | 15% | 19% | 14% | 11% | 8% | 7% | 7% | 6% | 4% |
| | 4 | 5% | 9% | 14% | 19% | 15% | 12% | 10% | 8% | 5% | 4% |
| | 5 | 3% | 6% | 11% | 15% | 17% | 15% | 13% | 9% | 6% | 3% |
| | 6 | 2% | 6% | 9% | 12% | 16% | 18% | 15% | 11% | 7% | 3% |
| | 7 | 2% | 4% | 7% | 9% | 14% | 16% | 19% | 15% | 9% | 4% |
| | 8 | 3% | 4% | 6% | 8% | 9% | 13% | 17% | 18% | 14% | 7% |
| | 9 | 4% | 5% | 6% | 6% | 7% | 8% | 10% | 15% | 22% | 17% |
| | 10 (High SR Exposure) | 6% | 6% | 5% | 4% | 4% | 4% | 5% | 8% | 17% | 41% |

**Table 10 Short Risk Exposure and Hedge Fund Skills**

This table reports the average hedge fund skills of short risk-exposure-sorted decile portfolios. Each month for each hedge fund with at least 24 returns observations in the past 36 months, short risk exposure (SR exposure) is estimated by regressing the fund excess returns on the short risk factor, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor-Stambaugh (2003) liquidity factor. As to the fund skill measures, each month for each hedge fund with at least 24 returns observations in the past 36 months, Titman and Tiu (2011)'s $R^2$ is estimated by regressing fund returns on the Fung and Hsieh (2004) seven factors. For each hedge fund with at least 30 return observations over the sample period, the timing abilities with respect to market return, volatility, and liquidity are estimated by the following regression.

$$Ret_{i,t} = a_0 + a_1 MKT_t + a_2 MKT_t \times I\,\{StateHigh_t\} + a_3 LIQUIDITY_t + a_4 SMB_t + a_5 UMD_t + a_6 PTFSBD_t + a_7 PTFSFX_t + a_8 PTFSCOM_t + a_9 \Delta TERM_t + a_{10} \Delta CREDIT_t + e_{i,t}$$

where $Ret_{i,t}$ is the excess return of fund $i$ in month $t$; $MKT_t$ is the market factor; $I\,\{StateHigh_t\}$ is a dummy variable that equals one when the market state variable in month $t$ is greater than its time series mean and zero otherwise, where the market state variable is market return, volatility, or liquidity. The coefficient $a_2$ measures market timing ability. Other control factors include the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| Portfolio | Titman and Tiu's (2011) $R^2$ | Market Timing Coefficient ($a_2$) Mkt Ret | Mkt Vol | Mkt Liq |
|---|---|---|---|---|
| 1 (Low SR Exposure) | 0.54 | 0.12 | -0.14 | 0.03 |
| 2 | 0.54 | 0.08 | -0.12 | 0.02 |
| 3 | 0.53 | 0.05 | -0.09 | 0.02 |
| 4 | 0.52 | 0.03 | -0.09 | 0.03 |
| 5 | 0.50 | 0.03 | -0.08 | 0.02 |
| 6 | 0.48 | 0.03 | -0.07 | 0.02 |
| 7 | 0.47 | 0.03 | -0.08 | 0.02 |
| 8 | 0.45 | 0.04 | -0.09 | 0.02 |
| 9 | 0.45 | 0.06 | -0.10 | 0.03 |
| 10 (High SR Exposure) | 0.46 | 0.11 | -0.13 | 0.03 |
| High - Low | -0.08*** | -0.02 | 0.01 | 0.00 |
| *(t-stat)* | (-4.69) | (-1.31) | (0.89) | (-0.12) |

**Table 11 Monthly Returns of Short Risk Portfolios: Conditioning on Fund Skills**

Starting from February 1999, for each month, I form 25 (5×5) equal-weighted portfolios formed by first sorting into quintiles on the basis of Titman and Tiu (2011)'s $R^2$ measure of fund skills and then sorting into quintiles based on the short risk exposure (SR exposure). I hold portfolios for one month and calculate portfolio returns. In each month for each hedge fund with at least 24 returns observations in the past 36 months, SR exposure is estimated by regressing the fund excess returns on the short risk factor, controlling for the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor-Stambaugh (2003) liquidity factor. Titman and Tiu (2011)'s $R^2$ is estimated by regressing fund returns on the Fung and Hsieh seven factors. Panel A presents monthly returns of portfolios, and Panel B presents monthly alphas of portfolios. Alpha is estimated based on the monthly time series of the portfolio returns relative to the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Both monthly excess return and alpha are reported in percent. Newey-West (1987) t-statistics are reported in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | | *SR Exposure* | | | | | |
|---|---|---|---|---|---|---|---|
| | | 1 (Low SR Exposure) | 2 | 3 | 4 | 5 (High SR Exposure) | Spread (High - Low) |
| *Panel A: Monthly returns for portfolios formed by conditioning on fund skills* | | | | | | | |
| Titman and Tiu's (2011) $R^2$ | 1 (Low $R^2$) | 0.39 | 0.38 | 0.40 | 0.57 | 0.83 | 0.44** |
| | | (3.46) | (3.42) | (3.85) | (4.35) | (4.38) | (2.72) |
| | 2 | 0.26 | 0.25 | 0.34 | 0.36 | 0.70 | 0.44*** |
| | | (1.54) | (2.26) | (2.99) | (2.81) | (3.82) | (2.95) |
| | 3 | 0.17 | 0.19 | 0.33 | 0.29 | 0.60 | 0.42*** |
| | | (0.97) | (1.37) | (2.51) | (2.00) | (2.93) | (2.98) |
| | 4 | 0.17 | 0.18 | 0.30 | 0.32 | 0.56 | 0.39** |
| | | (0.72) | (1.11) | (1.92) | (2.00) | (2.32) | (2.15) |
| | 5 (High $R^2$) | 0.19 | 0.21 | 0.24 | 0.47 | 0.57 | 0.38** |
| | | (1.15) | (0.98) | (1.20) | (2.06) | (2.59) | (2.09) |
| *Panel B: Monthly alphas for portfolios formed by conditioning on fund skills* | | | | | | | |
| Titman and Tiu's (2011) $R^2$ | 1 (Low $R^2$) | 0.26 | 0.34 | 0.26 | 0.31 | 0.67 | 0.41** |
| | | (2.50) | (5.54) | (3.54) | (3.76) | (4.94) | (2.47) |
| | 2 | 0.10 | 0.14 | 0.23 | 0.24 | 0.55 | 0.45** |
| | | (0.76) | (2.00) | (2.89) | (2.45) | (3.68) | (2.76) |
| | 3 | -0.07 | 0.05 | 0.19 | 0.14 | 0.42 | 0.49*** |
| | | (-0.61) | (0.59) | (2.33) | (1.49) | (2.82) | (3.30) |
| | 4 | -0.04 | 0.00 | 0.15 | 0.19 | 0.32 | 0.36** |
| | | (-0.27) | (0.04) | (1.80) | (1.98) | (2.31) | (2.10) |
| | 5 (High $R^2$) | -0.09 | -0.01 | 0.07 | 0.27 | 0.26 | 0.35** |
| | | (-0.80) | (-0.12) | (0.96) | (3.01) | (1.69) | (2.19) |

**Table 12 Short Risk Exposure and Mutual Fund Returns**

This table reports monthly returns of 10 equal-weighted portfolios of mutual funds sorted on the short risk exposure (SR exposure). In each month for each mutual fund with at least 24 returns observations in the past 36 months, SR exposure is estimated by regressing the fund excess returns on the short risk factor, controlling for the Fama-French three factors, the Carhart (1997) momentum factor, and the Pastor-Stambaugh (2003) liquidity factor. Based on the funds' SR exposures, I form 10 equal-weighted portfolios that are rebalanced each month. For each portfolio, alpha is estimated based on the monthly time series of the portfolio returns relative to the Fama-French three factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Both monthly excess return and alpha are reported in percentages. Newey-West (1987) t-statistics are reported in the parentheses.

| Portfolio | *SR Exposure* | *Excess Return* | *Alpha* |
|---|---|---|---|
| 1 (Low SR Exposure) | -0.17 | 0.27 | -0.06 |
| | | (1.09) | (-0.49) |
| 2 | -0.07 | 0.28 | -0.02 |
| | | (1.43) | (-0.15) |
| 3 | -0.04 | 0.10 | -0.16 |
| | | (0.59) | (-1.81) |
| 4 | -0.02 | 0.14 | -0.11 |
| | | (0.88) | (-1.35) |
| 5 | -0.01 | 0.34 | 0.05 |
| | | (2.25) | (0.61) |
| 6 | 0.01 | 0.32 | 0.01 |
| | | (1.90) | (0.11) |
| 7 | 0.02 | 0.20 | -0.11 |
| | | (1.14) | (-1.09) |
| 8 | 0.04 | 0.30 | -0.08 |
| | | (1.51) | (-0.68) |
| 9 | 0.06 | 0.36 | -0.02 |
| | | (1.99) | (-0.16) |
| 10 (High SR Exposure) | 0.15 | 0.38 | -0.11 |
| | | (1.56) | (-0.90) |
| Spread (High-Low) | 0.32 | 0.11 | -0.05 |
| *(t-stat)* | | (0.81) | (-0.29) |

**Table 13 Robustness Checks**

This table represents results of three robustness checks. Panel A presents monthly alphas of 10 equal-weighted portfolios of hedge funds sorted on the short risk exposure measured by the variance of option-implied loan fee. Panel B presents alphas for hedge fund portfolios sorted on short risk exposure (SR exposure) using an alternative performance evaluation models: Fama-French Five-factor model, including a market factor, a size factor, a value factor, a profitability factor, and an investment factor. Panel C reports monthly alphas of valued-weighted portfolios of hedge funds sorted on SR exposure. The value-weighted portfolio alphas are weighted by funds' monthly assets under management. Alpha is estimated based on the monthly time series of the portfolio returns, relative to the Fung and Hsieh (2004) seven factors, the Carhart (1997) momentum factor, and the Pastor and Stambaugh (2003) liquidity factor. Newey-West (1987) t-statistics are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

| | 1 (Low SR Exposure) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High SR Exposure) | Spread (High - Low) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Alternative measure of SR exposure - Variance of option-implied loan fee* | | | | | | | | | | | |
| *Alpha* | 0.02 | 0.11 | 0.15 | 0.19 | 0.24 | 0.26 | 0.28 | 0.31 | 0.33 | 0.43 | 0.41*** |
| | (0.64) | (1.59) | (1.94) | (2.21) | (2.41) | (2.58) | (2.86) | (3.07) | (3.35) | (3.51) | (2.77) |
| *Panel B: Fama-French Five Factor Model* | | | | | | | | | | | |
| *5-factor Alpha* | -0.05 | 0.08 | 0.04 | 0.09 | 0.15 | 0.20 | 0.25 | 0.24 | 0.26 | 0.44 | 0.49*** |
| | (-0.46) | (1.18) | (0.61) | (1.26) | (2.02) | (2.61) | (3.16) | (2.69) | (2.72) | (3.11) | (2.91) |
| *Panel C: Value-weighted portfolio returns* | | | | | | | | | | | |
| *Alpha* | 0.09 | 0.15 | 0.09 | 0.12 | 0.14 | 0.20 | 0.13 | 0.23 | 0.22 | 0.33 | 0.24** |
| | (0.92) | (2.13) | (1.42) | (1.95) | (2.01) | (2.53) | (1.67) | (2.81) | (2.47) | (2.51) | (2.03) |