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Why do Low R2 Hedge Funds have Low R2? An Empirical Study of the Performance and Risk of Low R2 Funds

Arnab Banerjee

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Why do Low R^2 Hedge Funds have Low R^2? An Empirical Study of the Performance and Risk of Low R^2 Funds

by

Arnab Banerjee

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ACCEPTANCE

This dissertation was prepared under the direction of the *ARNAB BANERJEE* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

Why do Low R^2 Hedge Funds have Low R^2? An Empirical Study of the Performance and Risk of Low R^2 Funds

by

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In this study, I examine whether low R^2 funds are exposed to higher equity systematic tail risk that is not accounted for in the existing multi-factor models used to evaluate hedge funds. With a parsimonious set of risk factors that includes systematic tail risk, I show that there is a significant increase (about 12%) in the R^2 for funds in the lowest quintile of R^2. In contrast, the increase in R^2 for funds in the other quintiles of R^2 is relatively modest (about 2%). Moreover, I show that the spreads between the future performance of low and high R^2 funds narrows by about 9% after accounting for the systematic tail risk factor. I also show that 90% of the decrease in future performance spread is driven by accounting for tail risk in the low R^2 funds. My results provide evidence that superior performance of low R^2 funds may not be entirely attributable to higher managerial skill, and that systematic tail risk of such funds can partially explain why they perform well.

INDEX WORDS: Hedge Funds, Correlation, Factor Models, Tail Risk.

I INTRODUCTION

"Our results indicate that factor models fail to measure systematic risk in over one-third of funds in commercial databases. These zero- R^2 funds appear to feature substantial exposure to an omitted systematic risk factor…" Bollen (2013)

Finding talented hedge fund managers is a difficult task. Among other metrics, institutional investors look at past performance, fund characteristics and low correlation to the overall market to identify managers that have a better chance of outperforming in the future. In my paper, I provide new evidence that funds with low R^2 values have greater equity systematic tail risk, suggesting the presence of an omitted factor in the model to estimate R^2.

The R^2 (adjusted R-square) of a fund, derived from regressing a fund's excess returns (in excess of the risk free rate) on a broad set of risk factors, tells us how closely the fund returns can be explained by the various risk factors. More precisely, R^2 is a measure of the fraction of fund's return variance that can be explained by the returns on the risk factors. Returns of the funds that follow unique investment strategies tend to be less correlated with the returns on systematic risk factors on an average, and hence have low R^2 values. So investors favor low R^2 funds over high R^2 funds because the former have a better chance of outperforming the latter, reason being low R^2 is attributed to higher managerial skill.[1]

My primary research question is: do funds with low R^2 exhibit greater systematic tail risk? A related question that I address is: how much of the superior future performance of hedge funds with low R^2 can be explained by their exposure to systematic tail risk? The academic literature

[1] "Despite the challenges in performance measurement, the most interesting feature of hedge funds is that they are thought of as nearly pure "bets" on manager skill", Goetzmann, Ibbotson and Brown (1995)

examining the relation between fund R^2 and future fund performance is quite extensive and rich. Titman and Tiu (2011, henceforth T-T) find that low R^2 can be linked to managerial skill as the performance of low R^2 funds is better than high R^2 funds. They also find that R^2 and fund fee have a negative correlation. They find that investors are ready to pay higher fees for low R^2 funds that exhibit low correlation with systematic risk factors. Amihud and Goyenko (2013) show a similar result for mutual funds, i.e., selectivity as measured by (1-R^2) is directly proportional to future fund performance even after controlling for funds' past performance, characteristics, and style. Several other studies that use measures similar to R^2, document similar findings. According to Sun, Wang, and Zheng (2012), funds that have higher strategy distinctiveness, SDI tend to be low R^2 funds, and they implement innovative strategies. In contrast, funds that have low SDI (high R^2) follow common investing themes and are more likely to follow other funds (herding mentality). There is also evidence that active management as measured by difference in portfolio and benchmark composition (weights) has a positive effect on mutual fund performance as shown in Brands, Brown, and Gallagher (2006), Kacperczyk, Sialm, and Zheng (2005), Cremers and Petajisto (2009), and Cremers et al. (2011).

There can be many reasons behind funds having low R^2 values. According to Sharpe (1992), style regression can attribute a manager's returns to asset classes only if the fund returns are correlated to the asset class returns. Fung and Hsieh (1997) argue that Sharpe's style regression is more suitable for buy and hold returns on asset classes and may not be appropriate for performance attribution in hedge funds. They attribute the low explanatory power of factor model regressions to the fact that hedge funds take positions in exotic securities that are not captured by traditional buy-and-hold risk factors. Another reason being hedge funds employ dynamic strategies that are associated with high turnover. One way to improve explanatory power is to construct factors that can capture the risks of different hedge fund trading strategies (see Fung and Hsieh (2001); Agarwal and Naik (2004); Duarte, Longstaff, and Yu (2007); Buraschi, Kosowski, and Trojani (2010); and Agarwal, Fung, Loon, and Naik (2011)). Another way to improve explanatory power of factor models is to allow factor exposures to vary over time to accommodate changes in hedge fund strategy as shown by Bollen and Whaley (2009) and Patton and Ramadorai (2013).

Despite the various attempts to improve the explanatory power of models for hedge funds, there remains a possibility that the existing models may be missing a systematic risk factor. According to Bollen (2013), one-third of the funds in a broad sample have R^2 that is insignificantly different from zero. Moreover, he shows that zero R^2 hedge funds still have systematic risk which is not being captured by the multifactor models possibly because of a missing factor. T-T observe that the variance in the returns of a portfolio of low R^2 funds cannot be explained by the set of common factors shown to be important in the prior hedge fund literature. They find that though the returns of low R^2 funds don't correlate highly with the returns of the common factors, they do show high correlation amongst themselves. They acknowledge the possibility of missing factors: "this observation is consistent with the presence of additional common factors to which the hedge funds tend to be exposed."

Motivated by these observations, I address the following questions in my study. First, is there greater systematic tail risk in low R^2 funds that can partially explain why they may perform better in the future? In other words, are the results from T-T driven by failure to account for greater systematic tail risk of funds with low R^2? Can a systematic tail risk factor help explain the difference between the future performance of low R^2 funds and high R^2 funds?

What is unique about systematic tail risk factor that is not captured by standard hedge fund factor models? Systematic tail risk factor provides a measure that tells us how susceptible the fund is to extreme downturns in the market. In other words, does the fund experience drawdowns that coincide with market drawdowns, and how severe the drawdowns are when compared to those of the market. Agarwal, Ruenzi, and Weigert (2016) propose a new measure of systematic tail risk that can explain future hedge fund performance. This is consistent with the findings of Bali, Brown, and Caglayan (2012) who provide evidence that the main driver of fund performance is systematic risk and not idiosyncratic risk. The key takeaway here is that systematic tail risk factor is priced in hedge funds (i.e., has a premium attached to it) but idiosyncratic tail risk is not rewarded by the market.

I begin my analysis by examining the relationship between fund R^2 and tail risk for all equity oriented hedge funds in my sample. The starting point of my analysis is fund R^2 values calculated using the same methodology and factor set as used by T-T. Based on the stepwise regression results, I then choose a candidate factor (MSCI EAFE index) for tail risk calculation based on high significance level (highest proportion of T-Stats greater than 2.33 when compared to other factors) and hit rate (selected 28% of the time in the stepwise regression). I then calculate tail risk for this factor based on the methodology prescribed by Agarwal, Ruenzi, and Weigert (2016).

I perform univariate sort on fund R^2 and tail risk to show that low R^2 funds have significantly higher tail risk than high R^2 funds. This result provides evidence that the factor model used to calculate fund R^2 is not able to capture this new kind of risk. While the stepwise model is able to capture the linear dependence between hedge fund returns and the factor returns but it is not able to capture the left tail correlation that is reflected in the tail risk factor.

Next I show that aggregated fund performance has a negative relationship to fund R^2. I confirm the findings from T-T that low R^2 funds have a higher performance (12-month forward looking alpha) than high R^2 funds. The Q1-Q5 performance spread between low and high R-squared funds is 6.78% annually and it is statistically significant at 1% confidence interval. This finding is consistent with the academic literature, which shows that low R^2 funds outperform high R^2 funds and this out-performance persists over time.

Next I examine the cross sectional determinants of fund R-squareds (model specification based on T-T) to show that after controlling for size, log(age), lockup, number of non-linear factors selected in the stepwise regression, and residual kurtosis, *tail risk has a negative and significant predictive effect on* fund R^2. Moreover, the multivariate regression also confirm that tail risk is a significant predictor of fund R-squareds even after controlling for additional fund characteristics such as management and incentive fees, minimum investment, redemption period, notice period and indicator variables for leverage, high watermark, offshore domicile and hurdle rate as well as univariate risk measures like residual skewness. The adjusted R^2 increases from 17.3% (T-T specification) to 20% (augmented specification that includes tail risk and additional fund characteristics), an improvement of 15.6%.

In addition to skewness and kurtosis, there is a possibility that funds that have high tail risk may also exhibit high positive returns (fat right tails). I include max return (maximum returns over the past 24 months) as an independent variable, based on Bali, Brown and Caglayan (2015) to account for the possibility that right tail can also explain the effect of tail risk on fund R-squareds. I find that both max return and tail risk are significant predictors of fund R-squareds but they don't interact with each other. While maximum return is positively related to fund R-squareds, tail risk has a negative exposure to fund R-squareds. Separately I also confirm that max return is not correlated with tail risk (correlation is 0.0008). The adjusted R^2 after including max returns remained same (20.08%).

Next I show that by including a tail risk factor (return of a portfolio that is long funds that have high tail risk and short funds that have low tail risk) in the step wise regression, I can improve the fund R-squareds values across all five quintiles (on an average by 2.66% for the whole sample). When I do a conditional sort on previously estimated fund R-squareds without tail risk, I find that largest increase is for low R^2 funds (quintile 1) which goes up by 12.3% , followed by Q2 (up by 4.9%), Q3 (up by 2.52%), Q4 (up by 1.01%) and Q5 (flat). The funds that had low R-square values previously (average R^2 of 17.76%), now have an average R-square of 19.94%. The spread in Q5-Q1 R^2 values decreases by 2.3% and is statistically significant. I also show that on an average 6.2% of the low R^2 funds are no longer low R^2 when systematic tail risk factor is included in the step wise regression.

Finally I examine whether systematic tail risk factor can explain time-series variation in fund performance. I show that spreads in future performance (Q1-Q5) of low and high R^2 funds narrows from 6.78% to 6.21% after accounting for the systematic tail risk factor. Also 90% of the decrease in performance spread is primarily driven by drop in performance of low R^2 (Q1) funds.

This study makes several contributions to the literature. First, I show that systematic tail risk can partially explain the phenomenon of low R^2 hedge funds. I show that low R^2 funds have high systematic tail risk than high R^2 funds. I also provide evidence that hedge fund Q1-Q5 performance spread is probably upwardly biased in the absence of systematic tail risk factor.

Second, my paper adds to the extant literature on fund R^2 and performance. More specifically, I shed some light on the notion of "low correlation or R^2 can be attributed to manager skill". According to T-T, hedge funds that are better informed are more likely to take less systematic risk. The authors suggest that less confident hedge fund managers generate abnormal returns by taking more exposure to systematic or priced factors while skilled managers take more active bet in their portfolios (higher idiosyncratic risk). Sun et al. (2012) argue that funds that have low correlation to other funds in the same category/style generate higher risk adjusted returns and are better informed. My results provide evidence that superior performance of low R^2 funds may not be entirely attributable to higher managerial skill, and that systematic tail risk of such funds can partially explain why they perform well.

My findings have important implications for institutional investors that invest in hedge funds. Investors need to understand the different strategies employed by hedge funds and accordingly tailor the factor model they use to calculate fund R^2 (one size does not fit all). They need to augment their risk factor set with equity systematic tail risk (or other relevant factors) in order to identify funds that have low R^2. Investors can also use this framework to identify what type of systematic tail risk they are exposed to across different asset classes such as fixed income, commodity, currency etc. and assess whether they are getting compensated to hold this additional source of risk. Investors that hold low R^2 funds in their portfolios cannot ignore tail risk in their portfolio construction framework because it can lead to significant losses during periods of market shocks. Also in periods of high market uncertainty, investors can identify funds that have high systematic tail risk, and can put in hedges to control portfolio drawdowns.

I.1 Hypothesis Development

I develop and test two hypotheses based on my research questions.

Hypothesis I: Risk - Low R^2 funds have higher systematic tail risk exposure than high R^2 funds

According to Bollen (2013), “Developing a complete set may be a Sisyphean task, especially if the missing factor represents catastrophic losses during rare events, which by nature will be difficult to capture given the well-known data limitations of hedge funds.”

Hedge funds can be exposed to tail risk when they follow dynamic trading strategies that have a non-linear relationship with the broader market (Fung and Hsieh, 1997, 2001, 2004; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004). Tail risk can be difficult to diversify as per Brown and Spitzer (2006) and Brown, and Gregoriou, and Pascalau (2012). This dependence on dynamic trading strategies makes it difficult for factor models to capture the time-series variation (non-linear dependence) of hedge fund returns. Moreover with explosive growth in in the hedge fund industry, fund managers are constantly trying to come with new investment ideas and are keen to differentiate[2] themselves from other hedge funds. This leads to concentrated portfolios[3] and higher exposure to non-linear risks that are orthogonal to the standard hedge fund factors. This may increase their exposure to large negative shocks in the overall market. In such cases the fund managers are exposing themselves to higher systematic tail risk and this orthogonal risk can be captured by the systematic tail risk factor.

[2] SEI Report: Observed Marsha Roth, senior managing director with Angelo, Gordon & Co., “Differentiation is critically important for managers in order to get institutional investors to understand the value your fund brings to their portfolio. While differentiation is a simple concept, it is difficult to accomplish because of the proliferation of funds. It is important to educate investors about what you do and how you do it, and a key part of that differentiation is the team.” Source:http://www.seic.com/docs/IMS/SEI-HF-Paper-6-Ways-to-Adapt_US.pdf?cmpid=im-hf-fine-13.

[3] Goldman Sachs report: "Hedge fund portfolio density remains near record highs. Hedge fund returns continue to depend on the performance of a few key stocks. The typical hedge fund has 69% of its long-equity assets invested in its 10 largest positions. This statistic compares with 33% for the typical large-cap mutual fund, 22% for the average small-cap mutual fund, 18% for the S&P 500 and just 2% for the Russell 2000 Index." Source: http://www.businessinsider.com/hedge-fund-manager-turnover-and-concentration-2016-8

Hypothesis II: Performance - By including tail risk, the gap in the performance of low R^2 and high R^2 funds narrows

According to Bollen (2013), an omitted risk factor can create an upward biased estimate of hedge fund performance. By accounting for the premium associated with the tail risk factor, the risk adjusted return spread between low and high R^2 funds is expected to narrow. Agarwal, Ruenzi, and Weigert (2016) shows that the tail risk factor explains cross-sectional variation in hedge fund returns even after controlling for other risks such as correlation risk (Buraschi, Kosowski, and Trojani, 2014), liquidity risk (Aragon, 2007; Sadka, 2010; Teo, 2011), macroeconomic uncertainty (Bali, Brown, and Caglayan, 2014), volatility risk (Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009), and rare disaster concerns (Gao, Gao, and Song, 2014).

The rest of the paper proceeds as follows. Section 1 describes the data sources and variable construction. Section 2 investigates the relationship between R^2 and tail risk Section 3 studies the impact of tail risk factor on fund performance. Section 5 provides context behind my findings and results. Section 6 concludes.

II DATA SOURCES AND VARIABLE CONSTRUCTION

II.1 Data Sources

Data on individual hedge funds is obtained from a "union database" which is constructed by combining four commercial hedge fund databases: Eurekahedge, HFR, Lipper TASS, and Morningstar. The union database contains assets under management, net-of fee returns, and hedge fund characteristics such as lockup, notice period, management and incentive fees, redemption period, minimum investment amount, inception dates, hurdle rate, offshore domicile and fund strategies. The advantage of combining four databases is that it can correct for inconsistencies among the different databases and it forms a representative sample of the whole hedge fund industry.

Potential Biases in Hedge Fund Data:

The start date of my sample is 1994, the year in which commercial databases started to include failed funds, so there is no survivorship bias in my sample. Backfill bias can arise when fund managers self -report back-tested or past histories when they join a commercial database. Most often fund managers' report back filled history if they had superior performance during the early history of the fund. This can bias the early return history of the funds in the database (generally an upward bias). Despite the bias, I don't exclude early return history of each fund because I am interested in the time-series variation in hedge fund returns and how factors models can capture this dynamics. This approach is consistent with the methodology followed by Bollen (2013). Hedge fund databases also suffer from smoothening as in Getmansky, Lo, and Makarov (2004), misreporting as in Cassar and Gerakos (2011) and are subject to censoring Agarwal, Fos, and Jiang (2013). But problem of return smoothening is less severe in US equity hedge funds as pointed out by Bollen and Pool (2009). My sample is restricted to only equity oriented hedge funds that are denoted in US dollars, and I do not correct for return smoothening.

I only select equity-oriented funds in my sample. The selected fund strategies include 'Emerging Markets', 'Event Driven', 'Equity Long-Short', 'Equity Long Only', 'Equity Market Neutral', 'Short Bias' or 'Sector'. I also make sure that funds in my sample have at least 24 monthly return observations. I exclude funds that report in currencies other than US dollars. Finally I end up with 7,561 equity-oriented funds in my sample from January 1996 to December 2013. I report summary statistics of hedge funds' characteristics and excess returns (returns minus risk free rate) by fund strategy in Table 1.

Insert Table 1 here

The mean monthly excess return in my sample is 0.57% and it ranges from 0.75% (Long Only) to -0.24% (Short Bias). The mean AUM is about $160 million and it ranges from $286 million (Event Driven) to $37.2 million (Short Bias).

II.2 Variable Construction

Risk Factors:

I take the set of factors from T-T to run 24 month rolling window step wise regressions to produce estimates of fund R^2 and alpha (the regression intercept). The factors can be broadly classified as follows:

Domestic Equity Factors: The goal here is to capture variation in US equity returns. This includes the Russell 3000, NASDAQ and NAREIT indices, Fama and French (1993) size (SMB) and value (HML) factors and Jegadeesh and Titman (1993) momentum (UMD) factor.

International Equity Factors: This includes DAX, CAC 40, FTSE 100 Indices, the NIKKEI 225, the Morgan Stanley Capital International (MSCI) Index EAFE, and the Morgan Stanley Capital International Emerging Markets (MSCI EMF) Index.

Domestic Fixed Income factors: This includes Salomon Brothers five-year Index of Treasuries, Barclays Aggregate Bond Index, Ibbotson Associates default spread (DEF) and duration spread (TERM), Barclays Aggregate of Mortgage-Backed Securities, and Barclays Index of ten-year maturity municipal bonds.

International Fixed Income/Foreign Exchange factors: This includes Salomon Brothers Non-US Unhedged Dollar Index (to measure the strength of the dollar) and Salomon Brothers Non-US Weighted Government Bonds Index with a five- to seven-year duration (intermediate).

Commodity Factors: This includes oil (an average of three oil price indices), gold and Goldman Sachs Commodity Index.

Nonlinear factors: This includes Primitive Trend Following Strategies (PTFS) for bonds, stock, currencies, and commodities as in Fung and Hsieh (2001) and portfolios of in- and out-of-the-money calls and puts on the S&P 500 Index from Agarwal and Naik (2004).

As hedge fund strategies can change over time (they are dynamic), I include a large number of factors (both linear and non-linear) so that the stepwise regression model is able to capture variation in fund returns. Stepwise regression methodology to identify factors has been used by Liang (1999), Fung and Hsieh (2000, 2001), and Agarwal and Naik (2000, 2004). I use the forward selection method with probability of entry and exit that closely follows T-T methodology which "selects a parsimonious set of explanatory factors by adding factors sequentially based on their F -test significance, allows the data to select the set of factors for each fund that best explains that fund's returns."

I estimate various multifactor models specified as

$$R_{i,t} - r_f = \alpha + \sum_{k=1}^{K} \beta_{i,k}^{T} F_{k,t} + \epsilon_{i,t}^{T} \quad , t = t_0 , \ldots. , T$$

Where is r_f the risk-free rate, K is the number of factors selected by the stepwise algorithm and F represents the returns of factor portfolios. I aim to study the relationship between fund α and the fund R-squareds generated from the above step wise regressions.

Performance measures:

I calculate rolling 12 month forward alpha (performance) as specified in T-T.

It is calculated from aggregating monthly alpha from time t+1 to t+13 to calculate 12 month forward alpha.

I also calculate max return (trailing 24 month maximum returns) for all funds in my sample.

Tail risk measure:

I estimate tail risk for the MSCI EAFE Index using the methodology used by Agarwal, Ruenzi, and Weigert (2016), on a rolling 24 month window. For every fund and every trailing 24 month period, the two worst returns of the index and fund are calculated. [4] Then tail sensitivity measure is calculated as 1 (if both worst returns of the fund and the index coincide), 0.5 (only one of the worst returns coincide) or 0 (none of the worst returns coincide). Tail risk is then calculated as the product of tail sensitivity and ratio of the expected shortfall (average of two worst returns) of the fund and index.

Tail risk factor return:

I estimate the tail risk factor return by creating a monthly portfolio that goes long funds that have high tail risk and short funds that have low tail risk. The return of this portfolio is the proxy for the tail risk factor. This follows the same methodology Fama and French (1993) size (SMB) and value (HML) factors.

II.3 Summary Statistics

Table 2 presents summary statistics of R-square measure, annualized alpha and number of factors selected from the stepwise regressions.

[4] Expected shortfall at 5% confidence interval amounts to 1.2 months which is approximated to two months

Insert Table 2 here

The mean Adj. R^2 for the whole sample is 58% while for Market Neutral funds that hedge out market risk, the mean Adj. R^2 is much lower around 44%. The mean annualized alpha in my sample is 2.2%. The median number of factors selected in the stepwise regression model is 3, and it rarely goes higher than 4 or 5. The main reason behind low number of factors is that the stepwise regression model doesn't allow large number of factors because of the cross-correlation between the independent risk factors. Also hedge funds hold concentrated portfolios, hence can only have exposure to a few risk factors. This observation is supported by Bollen (2013), who shows that funds with concentrated portfolios are more likely to have concentrated factor exposures. He reports that for low R^2 funds, the most important factor accounts for 89% of the explained variation in fund returns compared to 83% for high R^2 funds. These results are consistent with T-T who estimates the mean Adj. R^2 and median number of factors from stepwise regressions to be 54% and 3 respectively.

Table 3 presents the summary statistics of the top five factors selected in the step wise regression.

Insert Table 3 here

MSCI EAFE and the Russell 3000 index are the top two factors selected in the step wise regression. MSCI EAFE is slightly ahead since it has higher hit rate than Russell 3000 (28% vs. 27%) and it is also significant the most number of times (both at 1% and 5% confidence level). The other top factors are Fama and French (1993) size (SMB) and value (HML) factors and Jegadeesh and Titman (1993) momentum (UMD) factor. Based on the significance level and hit rate, I select MSCI EAFE as the candidate factor for estimating tail risk. The reason being if most funds have linear exposure to this factor, it is likely that they may be exposed to the left tail of this factor.

III RELATIONSHIP BETWEEN R-SQUARE AND TAIL RISK

I begin my analysis by conducting tests to analyze the relation between R-square and Tail risk.

III.1 Univariate Sort: R-square and Tail risk

In Table 4, I sort systematic tail risk on the fund R-square quintiles to understand the univariate relationship between them.

Insert Table 4

Consistent with my hypothesis I find that low R-square funds have higher tail risk than high R-square funds. Q1 R-square funds have the highest exposure to tail risk (3.93) and Q5 R-square funds have the lowest exposure to tail risk (0.52). The Q1-Q5 spread of 3.41 is statistically significant at 1% confidence interval.

Next I look at fund characteristics, other information such prime brokers etc. and style concentration of low R-square funds. The goal here is to understand why low R-square funds have more tail risk and are there any fund features that may point us to the reason behind their higher systematic tail risk.

Table 5 reports the fund characteristics for low R-square, high R-square and all funds in my sample. It also reports the Q1-Q5 spread and associated significance levels.

Insert Table 5

Univariate analysis of fund characteristics show that low R-square funds are on a relative basis smaller in size and younger than high R-square funds. These low R-square funds also charge higher fees (both management and incentive fees), employ more leverage, and have high lockup period, water mark, minimum investment levels and notice period. These results are consistent with the skill interpretation that low R-square funds are managed by skilled managers that are able to charge higher fees and negotiate better terms (higher lockup and notice period) with investors. Moreover low R-square funds have higher residual skewness and kurtosis. And the number of non-linear factors selected in the step wise regression for low R-square funds is lower than that of high R-square funds (this finding is consistent with T-T).

Table 6 reports information on prime brokers, auditors and fund administrators for both low and high R-square funds. It is not clear from the table if there are any significant differences between the two groups (low and high R-square funds) with regards to which prime brokers, auditors and administrators they use.

Insert Table 6

Table 7 reports the style concentration of low and high R-square funds and their associated tail risk.

Insert Table 7

It is interesting to note that low R-square funds have higher proportion of Event Driven, Market Neutral and Emerging Market strategy funds when compared to high R-square funds. This is intuitive because we know on an average Market Neutral funds are hedged and will have low R^2 compared to other funds. Also on relative basis Event Driven and Emerging Market funds have lower R^2, while Long Only and Short Bias have higher R^2. Moreover I find that low R^2 funds have higher tail risk across all strategies than high R^2 funds. This result is consistent with my *Risk* hypothesis.

III.2 Determinants of R-square

Table 8 represents the cross sectional determinants of R-square.

Insert Table 8

I estimate five different models as designated in table 5. Model 1 closely follows the

T-T specification where the independent variables are log (AUM), log (Age), lockup (includes lockup and redemption period), number of non-linear factors and kurtosis of residual from the stepwise regression. I cluster standard error by fund and time and include strategy dummies in the regression. I find no significant relationship between R-Square and size which confirms T-T. Also lockup has no linkage to R-square which is similar to T-T's findings. I include number of nonlinear factors in the regression to test whether hedge funds that take exposure to standard nonlinear factors have low R-square. Ingersoll, Spiegel, Goetzmann, and Welch (2007) find that some funds may try to game the system and implement nonlinear strategies to skew their performance. This can result in an artificial negative relationship with R-square and performance. Consistent with T-T, I find that number of nonlinear factors has a significant positive relationship with R-square. This finding suggests that funds that employ nonlinear strategies tend to have higher R-square, so they cannot game the system. The adjusted R^2 of the regression is 17.2% which is similar to what T-T reported (15.42%).

But contrary to T-T, I find that R-square is positively related to log (Age). This is intuitive because with age, funds grow more mature take less risks, stick to common investment themes and start to gather assets using their existing track record rather than focus on performance.

Also residual kurtosis has a significant negative exposure to R-Square meaning funds whose returns have fat tails (leptokurtic) are likely to have low R-Square.

Model 2 adds the tail risk factor as an additional independent variable. I find that tail risk is negatively related R-square which is consistent with my hypothesis and confirms the result from the univariate sort. The adjusted R^2 didn't change significantly from the previous specification.

Model 3 includes residual kurtosis, other fund characteristics such as management fee, incentive fee, notice period, minimum investments ($100,000) and indicator variables for leverage, high water mark, and offshore domicile. When taken together (tail risk and additional fund characteristics), the adjusted R^2 increases to 20% (an improvement of 15.6% over T-T specification). I find that residual skewness is negatively related to R-square. When I consider negative exposures for both residual skewness and kurtosis, I think the more the fund returns deviate from a normal distribution (fat tails and skewed distribution), it is more likely that R-square of the fund will be lower. I also find that incentive fee is negatively related to R-square which means low R-square funds charge higher fees than high R^2 funds. This result is consistent with T-T. The exposure for offshore domicile funds is also negative and significant at 1% confidence interval. Offshore is an indicator variable that is zero for funds located in the US and 1 for funds located outside the US. This means that offshore funds tend to have lower R-square (higher managerial skill) than onshore funds. This contradicts Goetzmann, Ibbotson and Brown (1995) who don't find any difference in managerial skill between offshore and onshore funds.

In Model 4, I add one more independent variable, max returns which is 24 month trailing maximum returns as in Bali, Brown and Caglayan (2015). According to Bali et al (2015), max return is a strong predictor of future returns even after controlling for fund characteristics and alternates measures of risk and performance. A potential concern is that funds that have fat right tails (max returns) may also influence fund R-square and I want to confirm that tail risk factor is still significant even after controlling for max returns. I find that both max return and tail risk are significant predictors of fund R-squareds but they don't interact with each other. While max return is positively related to fund R-squareds (which is a bit puzzling), tail risk has a negative exposure to fund R-squareds. Separately I also confirm that max return is not correlated with tail risk (correlations is 0.0008). Also I find that size is now related to fund R-square (significant at 1% level) which contradicts T-T. This means that larger hedge funds manage more diversified portfolios and as a consequence have higher R-square values. I think max returns and size may be interacting in a way that is making size more significant. The adjusted R^2 after including max returns remained same (20.09%).

According to Bali et al (2015) hedge funds have non-normal distribution of returns because they employ dynamic strategies that have nonlinear payoffs. Max return is trying to capture this nonlinear behavior in the right tail of hedge fund return distribution. So max returns may interact with some of the factors in the regression such as number of nonlinear factors, residual kurtosis and residual skewness. Also it is not clear how it interacts with size and it may have an effect on log (age) also since age and size are correlated. So in order to understand the interaction between tail risk and max returns, I run a simple model with just those two factors and the hedge fund characteristics (model 5). I find that tail risk is still significant and has a negative relationship with fund R-Square but max return is not related to fund R-square.

In summary I show that tail risk has a consistent significant negative exposure to R-square across all the different model specifications. It is a unique risk measure that influences fund R-square even after controlling for log (Age), size, and number of nonlinear factors, residual kurtosis, residual skewness, max returns and hedge fund characteristics. These results strongly support my first hypothesis *Risk*.

IV RELATIONSHIP BETWEEN R-SQUARE AND PERFORMANCE

I begin my analysis by conducting tests to analyze the relation between fund R-square and Performance (12 month forward looking alpha).

IV.1 Univariate Sort: R-square and Performance

In Table 6, I sort performance (12 month forward alpha) on the fund R-square quintiles to understand the univariate relationship between them.

Insert Table 9

I find that low R-square funds have higher performance (12 month forward alpha) than high R-square funds. The Q1-Q5 performance spread is 6.78% and it is statistically significant at 1% confidence level. These results are consistent with T-T who find that for Long-Short Equity funds the 12 month alpha spread (equally weighted) between low and high R-square funds is 7%.

IV.2 Conditional Sort: R-square and Re-estimated R-Square

Next I re-estimate the step wise regressions and include the tail risk factor as one of the candidate factors to choose from. Table 10 shows the re-estimated R-square values conditioned on the previously estimated fund R-square (without tail risk) quintiles.

Insert Table 10

I see an improvement in the fund R-squareds values across all five quintiles (on an average by 2.66% for the whole sample). Also the largest increase is for low R^2 funds (quintile 1) which goes up by 12.3%, followed by Q2 (up by 4.91%), Q3 (up by 2.52%), Q4 (up by 1.01%) and Q5 (flat). The funds that had low R^2 values previously (17.8%), now have an average R-square of 19.94%. Also the spread in Q5-Q1 R^2 values decrease from 71.63% to 69.35% and is statistically significant at the 1% confidence level.

So what percent of low R-square funds are no longer low R-square when systematic tail risk is taken into account? Table 11 reports the transition rates for low R-square funds.

Insert Table 11

Table 11 shows that about 6.2% of low R-square funds move to higher R-square quintiles after systematic tail risk is included in the step wise regression. 4.3% of low R-square funds move to quintile 2, 1.4% move to quintile 3, 0.4% move to quintile 4 and 0.1% move to quintile 5.

Finally I examine whether tail risk factor can explain time-series variation in fund performance. Table 12 shows re-estimated alpha values conditioned on the previously estimated fund R-square (without systematic tail risk) quintiles. I show that the spreads in future performance of low and high R^2 funds narrows from 6.78% to 6.21% after accounting for the systematic tail risk factor.

Insert Table 12

This is consistent with my *Performance* hypothesis and suggests that after taking into account the premium associated with the tail risk factor, the Q1-Q5 alpha spread between low and high R-square funds narrow down. Further the decrease in Q1-Q5 performance spread of 57bps is primarily driven by drop in performance of the Q1 alpha (51bps).

Table 12 also reports the systematic tail risk exposure for the different quintiles and significance levels of the exposures.

It makes sense that the tail risk factor exposure is positive for Q1 which explains why the alpha for Q1 went down. But alpha for Q2-Q5 went up and exposure to tail risk factor for these quintiles are negative. This is a counterintuitive result. Let's try to understand why this is the case. First, when I include tail risk factor in the stepwise regression, the new set of fund regressions are estimated from scratch hence the exposures for tail risk factor depends on how the tail risk factor is correlated with other risk factors in the regression. Second, not all funds have tail risk to begin with (this holds true for funds across all quintiles of R-square but more so for funds in Q2-Q5), so the distribution of tail risk across funds is asymmetric and this can play a role on the loadings of the long short tail risk factor for Q2-Q5 funds. Third, the negative exposure for Q2-Q5 can be partly explained by how the tail risk factor is constructed. It is the return of long short portfolio (rebalanced monthly) that is constructed by going long fund that have high tail risk and short funds that have low tail risk. I follow the same factor construction methodology as Fama and French (1993) use for constructing size (SMB) and value (HML) factors. Finally, one can argue that this result is similar to low value (quintile 5) stocks having negative slope to value factor (HML)[5]. It ties in with Table 4 and Exhibit 10.1, which shows that Q1 (low R-square funds) have the highest tail risk. Quintiles Q2-Q5 have low tail risk and they are not statistically different from each other (the distribution of tail risk across the different quintiles in asymmetric). So quintiles Q2-Q5 that have low tail risk have negative exposure to the tail risk factor.

Insert Exhibit 1

In summary, I show that after taking tail risk into account R-Square of funds increase across the board (low R^2 funds show highest increase) and Q1-Q5 performance spread goes down. These results strongly support my second hypothesis *Performance*.

[5] Fama and French, 1993

V DISCUSSION

In this paper, I accomplish two objectives. First, I show that low R^2 funds have higher systematic tail risk than high R^2 funds. Second, I provide evidence that the performance spread between low and high R^2 funds narrows when systematic tail risk is taken into consideration.

Academic literature argues that the level of active management in a fund can have a positive effect on fund performance.[6] Studies have shown that higher idiosyncrasy (low R^2) in hedge fund returns signify higher managerial skill and activity.[7] I show that 6.2% of low R^2 funds are no longer low R^2 when you include systematic tail risk. This suggests that the definition of low R^2 funds (and how that relates to managerial skill) can change in case there is an omitted factor in the factor model used to calculate R^2 values. Also, low R^2 is not a necessary condition for high managerial skill or performance but it has been shown in the literature that there is a strong relation between the two.

I show that the performance spread between low and high R^2 funds can be upwardly biased when there is an omitted factor such as the systematic tail risk. So the outperformance of low R^2 funds (evidence of managerial skill) can be partially explained by systematic tail risk. The performance spread narrows from 6.78% to 6.21%, a decrease of 57bps by including systematic tail risk. More importantly 90% of the decrease in future performance is driven by low R^2 funds.

Even after accounting for tail risk, the performance gap between low and high R^2 funds continues to be high. Bollen (2013) shows that portfolios constructed from zero R^2 funds have half the volatility of other funds (that have high R^2). He suggests that there may be one or more omitted factors that is driving the volatility of zero R^2 funds. So there can be other kinds of risks such as

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[6] Brands, Brown, and Gallagher, 2006; Kacperczyk, Sialm, and Zheng, 2005); Cremers and Petajisto, 2009; and Cremers et al.,2011.
[7] Titman and Tiu, 2011; Sun, Wang, and Zheng, 2012; Amihud and Goyenko, 2013.

operational risk, and other non-linear sources of risk in addition to systematic tail risk that a linear factor model is not able to capture. Alternatively, the performance gap may be a true measure of the ability and skill of the hedge fund manager to generate abnormal returns.

Continuing on the theme of volatility of low R^2 funds, next I discuss the implications of standard portfolio diversification such as mean-variance framework within the context of investing in low R^2 funds which have high tail risk. Hedge funds that follow dynamic trading strategies have a nonlinear relation with the broader market.[8] As a result such funds can be exposed to tail risk which can be difficult to diversify.[9] Agarwal and Naik (2004) compare two portfolio construction methods, traditional mean-variance framework and mean-conditional value-at-risk[10] (M-CVaR) framework to understand the extent of under-estimation of tail risk for mean-variance optimal portfolios. They find that underestimation of tail risk can range from 12% to 54% (for range of confidence levels from 90% and 99%) for mean-variance optimal portfolios. Moreover, this underestimation is more pronounced for low volatility portfolios which is the case for a portfolio of low R^2 funds. This finding has important implications for investors that hold low R^2 funds in their portfolios, since ignoring tail risk in their portfolio construction framework can lead to significant losses during periods of market shocks.

Next I try to provide some intuition from the prior literature about the holdings of low R^2 hedge funds that can contribute towards high tail risk. Agarwal, Ruenzi, and Weigert (2016) analyze long equity and option positions from 13F filings of hedge funds to show that these positions in tail-sensitive stocks and put options can partially explain why these funds have high tail risk. They also find that higher leverage in funds can contribute to higher tail risk.

[8] Fung and Hsieh, 1997, 2001, 2004; Mitchell and Pulvino, 2001; Agarwal and Naik, 2004.
[9] Brown and Spitzer, 2006; Brown, Gregoriou, and Pascalau, 2012.
[10] Mean-conditional Value-at-risk is same as Expected Shortfall which is used in calculating systematic tail risk.

V.1 Implications for Practice

So how are these research findings relevant for a practitioner such as a fund of fund manager? It is clear that low R^2 funds are doing something unique that sets them apart from other funds and they are able to deliver significant future performance.

Funds that are low R^2 cannot remain low R^2 for the life of the fund. Through time low R^2 funds which are usually smaller in size and younger in age, gather more assets and become mature. This observation is consistent with my findings that show log (age) is positively related to fund R^2. Along the way their investment strategy evolves from unique to more traditional investments and their R^2 increases over time. So in order to generate superior abnormal returns, one has to keep investing in low R^2 funds and incur high turnover which can be prohibitively costly. Given that standard lockup periods are about a year, one has to rebalance their portfolio of low R^2 funds every year and that may not be feasible.

Another related concern is persistence of performance. How can these low R^2 funds keep generating high abnormal returns? Berk and Green (2004) show that for the mutual fund industry, skill of the fund manager is a scarce resource and as the fund increases in size (due to higher fund flows that follow past performance), its expected performance going forward goes down. In the equilibrium, investors continue to invest in the fund till the performance of the fund remains competitive in the marketplace. Thus they argue that performance cannot remain persistent over time. Glode and Green (2011) argue that hedge funds are different from mutual funds since they are private, don’t have to disclose information, and have less oversight than mutual funds or public companies. They link persistence in performance to secrecy (organizational form of hedge funds) in the sense that performance can attributed to unique strategies/techniques in addition to managerial skill.

Another concern is that investing in low R^2 funds can be risky since they have high tail risk, as my study shows. Though low R^2 funds tend have low volatility[11], measures like standard deviation (second moment) of returns is not able to capture systematic tail risk which can be a function higher moments such as skewness and kurtosis. Also not all low R^2 funds have tail risk, so there is some diversification effect that can be gained by combining a bunch of low R^2 funds. As I noted earlier in this section, a portfolio construction method[12] that takes into expected shortfall is more appropriate in this case.

Based on my findings, here are my suggestions for a fund of fund manager that wants to construct a portfolio of low R^2 funds with superior risk return profile.

- Identify low R^2 funds that have no or limited exposure to systematic tail risk. In my study I have only examined equity systematic tail risk but low R^2 funds can have systematic tail risk to commodity, currency or fixed income factors also.
- Use an appropriate portfolio construction methodology that takes into account tail risk such as mean-conditional value-at-risk framework rather than the mean-variance framework, and controls for excessive turnover and trading costs to create a fund of low R^2 funds.
- Use fund due diligence and qualitative information about the manager and the hedge fund strategy to complement the quantitative research to select the funds for investment. For instance low R^2 funds may have higher operational risk that includes return misreporting among other attributes.

To summarize, in this section, I provide some context behind my key findings and how that relates to extant literature. I discuss implications for portfolio diversification and provide some intuition on portfolio holdings of low R^2 funds. I also provide suggestions for practitioners such as

[11] Bollen, 2013
[12] Mean-conditional value-at-risk (M-CVaR) framework (Agarwal and Naik, 2004)

fund of fund managers as to how they can leverage my findings to construct more efficient fund of funds.

VI CONCLUSION

I make two primary contributions in this paper. First I show that low R^2 funds have higher equity systematic tail risk that is not accounted for in existing multi-factor models used to evaluate hedge funds. Second, I show that the spreads between the future performance of low and high R^2 funds narrows by about 9% after accounting for the systematic tail risk factor. These findings are consistent with my *Risk* and *Performance* hypotheses respectively. I also provide evidence that superior performance of low R^2 funds may not be entirely attributable to higher managerial skill, and that systematic tail risk of such funds can partially explain why they perform well.

My results are valuable both from an academic and fund due diligence viewpoint. It is possible that low R^2 funds may have exposure to one or more omitted factors but if the fund analyst can tailor the factor model to the specific hedge fund strategy, then she will have a better chance of capturing a larger fraction of the variation in fund returns. My findings are important to investors that hold portfolio of low R^2 funds and want to construct efficient portfolios to manage their tail risk exposures.

There are a number of limitations of this study which may lead to further research. The systematic tail risk factor is constructed by going long hedge funds that have high tail risk and short funds that have low tail risk. It is not feasible to short hedge funds so constructing this factor from a piratical standpoint can be difficult. One can take only the long side of the tail risk factor to construct an investible risk factor and replicate the study. My study can be extended to non-equity oriented hedge funds to understand the implications of systematic tail risk on fund R^2 for multi-strategy, fund of funds, CTAs and macro hedge funds. Moreover the T-T risk factors can be supplemented by other risk factors such as correlation risk[13], liquidity risk[14], macroeconomic

[13] Buraschi, Kosowski, and Trojani, 2014
[14] Aragon, 2007; Sadka, 2010; Teo, 2011

uncertainty[15], volatility risk[16] and rare disaster concerns[17] to make the factor set more robust and representative of all the different types of risk. The limitations of stepwise regression can be overcome with more sophisticated methods such as LASSO or Elastic-Net regression etc.

[15] Bali, Brown, and Caglayan, 2014
[16] Bondarenko, 2004; Agarwal, Bakshi, and Huij, 2009
[17] Gao, Gao, and Song, 2014

APPENDICES

Appendix A Tables

Table 1: Summary Statistics

This table reports the AUM ($ mil), Age in months, excess returns (monthly), management fee, incentive fee, minimum investment ($100,000), lockup calculated as log (1+redemption/30+lockup/30) as in Titman and Tiu (2011), redemption period (days) and indicator variables leverage, high water mark and hurdle rate for all hedge funds in my sample from January 1996 to December 2013.

Style	Variable	Mean	Std. Dev	25%	Median	75%	N
Event Driven	AUM ($ mil)	286.26	743.16	25.2	72	210	37110
	Age	88.37	59.99	42	70	118	43454
	excess returns	0.50%	4.31%	-0.61%	0.50%	1.75%	43452
	mfee	1.48	0.47	1	1.5	2	42707
	ifee	18.83	4.29	20	20	20	43283
	mininv ($100,000)	14.27	21.36	5	10	10	42305
	lockup	1.88	1.08	0.69	1.95	2.77	43454
	offsh	0.50	0.50	0	1	1	43454
	lev	0.56	0.50	0	1	1	32050
	redem	125.67	120.40	30	90	90	41719
	hwm	0.84	0.37	1	1	1	42314
	hurdrate	0.27	0.44	0	0	1	43454
Style	**Variable**	**Mean**	**Std. Dev**	**25%**	**Median**	**75%**	**N**
Emerging Markets	AUM ($ mil)	132.77	342.98	14.68	39.95541	116	19194
	Age	74.56	45.18	40	62	96	25821
	excess returns	0.65%	7.74%	-2.22%	0.59%	3.65%	25821
	mfee	1.62	0.42	1.5	1.5	2	24489
	ifee	17.67	5.15	15	20	20	24634
	mininv ($100,000)	6.17	16.77	1	2	5	25008
	lockup	0.95	0.94	0.21	0.69	1.39	25821
	offsh	0.88	0.32	1	1	1	25821
	lev	0.62	0.49	0	1	1	16968
	redem	52.25	60.98	30	30	90	22574
	hwm	0.70	0.46	0	1	1	23626
	hurdrate	0.16	0.37	0	0	0	25821
Style	**Variable**	**Mean**	**Std. Dev**	**25%**	**Median**	**75%**	**N**

Long Only	AUM ($ mil)	176.34	431.51	15.8	49.9555	162.25	15330
	Age	80.86	49.38	42	67	108	21682
	excess returns	0.75%	6.85%	-1.67%	0.68%	3.29%	21682
	mfee	1.40	0.45	1	1.5	1.75	20813
	ifee	14.75	7.70	10	20	20	20993
	mininv ($100,000)	40.61	406.78	1	1	10	19485
	lockup	0.99	1.07	0.10	0.69	1.39	21682
	offsh	0.75	0.43	1	1	1	21682
	lev	0.50	0.50	0	1	1	3194
	redem	52.74	69.60	30	30	90	19497
	hwm	0.70	0.46	0	1	1	20417
	hurdrate	0.38	0.49	0	0	1	21682

Style	**Variable**	**Mean**	**Std. Dev**	**25%**	**Median**	**75%**	**N**
Long Short	AUM ($ mil)	135.14	452.47	10.87	34.7	108.4	153190
	Age	85.08	64.32	42	68	111	189373
	excess returns	0.61%	21.30%	-1.67%	0.49%	2.80%	189388
	mfee	1.37	0.53	1	1.5	1.5	185130
	ifee	18.39	5.28	20	20	20	185954
	mininv ($100,000)	7.90	16.50	2	5	10	183728
	lockup	1.53	1.10	0.69	1.39	2.77	189393
	offsh	0.47	0.50	0	0	1	189393
	lev	0.63	0.48	0	1	1	123177
	redem	82.17	93.47	30	90	90	177837
	hwm	0.83	0.37	1	1	1	184224
	hurdrate	0.30	0.46	0	0	1	189393

Style	**Variable**	**Mean**	**Std. Dev**	**25%**	**Median**	**75%**	**N**
Market Neutral	AUM ($ mil)	172.27	438.51	10.13	39.69658	148	17445
	Age	73.32	48.70	37	58	94	20579
	excess returns	0.26%	3.75%	-0.82%	0.24%	1.36%	20579
	mfee	1.38	0.54	1	1.25	2	19859
	ifee	18.04	6.25	20	20	20	19867
	mininv ($100,000)	21.27	64.09	2.5	10	10	20251
	lockup	1.13	0.94	0.69	0.69	1.39	20579
	offsh	0.48	0.50	0	0	1	20579
	lev	0.52	0.50	0	1	1	16392
	redem	50.57	48.15	30	30	90	19063

Style	Variable	Mean	Std. Dev	25%	Median	75%	N
	hwm	0.75	0.43	0	1	1	19944
	hurdrate	0.26	0.44	0	0	1	20579

Style	Variable	Mean	Std. Dev	25%	Median	75%	N
Short Bias	AUM ($ mil)	37.18	48.49	7.465	20	49.55	2536
	Age	84.77	51.04	44	73	113	3117
	excess returns	-0.24%	6.73%	-3.27%	-0.10%	2.68%	3116
	mfee	1.31	0.50	1	1	1.5	2962
	ifee	18.27	7.37	20	20	20	3072
	mininv ($100,000)	6.92	12.84	2.5	5	10	3117
	lockup	1.49	1.03	0.69	1.39	2.77	3117
	offsh	0.45	0.50	0	0	1	3117
	lev	0.56	0.50	0	1	1	2598
	redem	78.34	66.68	30	90	90	2934
	hwm	0.72	0.45	0	1	1	3117
	hurdrate	0.23	0.42	0	0	0	3117

Style	Variable	Mean	Std. Dev	25%	Median	75%	N
Sector	AUM ($ mil)	120.40	258.67	10	29.14	100	8127
	Age	70.55	50.26	36	54	88	8808
	excess returns	0.44%	7.53%	-2.26%	0.37%	3.12%	8807
	mfee	1.40	0.43	1	1.5	1.75	8604
	ifee	19.34	3.23	20	20	20	8707
	mininv ($100,000)	10.59	20.82	2.5	10	10	8790
	lockup	1.99	1.01	1.39	2.30	2.77	8808
	offsh	0.30	0.46	0	0	1	8808
	lev	0.64	0.48	0	1	1	8744
	redem	104.91	111.06	30	90	90	8764
	hwm	0.90	0.30	1	1	1	8808
	hurdrate	0.00	0.02	0	0	0	8808

Style	Variable	Mean	Std. Dev	25%	Median	75%	N
All Funds	AUM ($ mil)	160.73	493.63	12.3	40	125.57	252932
	Age	83.19	60.15	41	67	109	312834
	excess returns	0.57%	16.98%	-1.47%	0.48%	2.58%	312845
	mfee	1.41	0.51	1	1.5	1.75	304564
	ifee	18.15	5.48	20	20	20	306510
	mininv ($100,000)	11.72	106.00	1.5	5	10	302684
	lockup	1.48	1.10	0.69	1.39	2.77	312854

offsh	0.52	0.50	0	1	1	312854
lev	0.60	0.49	0	1	1	203123
redem	82.69	95.05	30	90	90	292388
hwm	0.81	0.39	1	1	1	302450
hurdrate	0.28	0.45	0	0	1	312854

Table 2: Summary Statistics of Factors Models – Stepwise Regressions
This table reports the estimated R-Squareds, annualized alpha and number of factors selected in the step wise regression. The R-squareds are calculated from stepwise regressions using the entire history of each fund on a rolling 24 months window. Funds are divided by strategy type. The sample data used span from January 1994 to December 2013.

Style Master	Variable	Mean	Std. Dev	p25	Median	p75
Event Driven	Adj R^2	0.53	0.26	0.35	0.56	0.74
	Alpha	0.03	0.34	-0.08	0.03	0.14
	No. of Factors	2.66	1.65	1	2	4
Emerging Markets	Adj R^2	0.58	0.24	0.43	0.63	0.78
	Alpha	0.01	0.57	-0.24	0.00	0.23
	No. of Factors	2.79	1.62	2	3	4
Long Only	Adj R^2	0.61	0.26	0.43	0.67	0.83
	Alpha	0.01	0.51	-0.17	0.01	0.18
	No. of Factors	2.78	1.65	2	3	4
Long Short	Adj R^2	0.60	0.25	0.44	0.65	0.81
	Alpha	0.02	1.42	-0.15	0.01	0.18
	No. of Factors	2.88	1.65	2	3	4
Market Neutral	Adj R^2	0.44	0.26	0.24	0.44	0.63
	Alpha	0.02	0.36	-0.08	0.02	0.13
	No. of Factors	2.37	1.62	1	2	3
Short Bias	Adj R^2	0.71	0.23	0.59	0.78	0.89
	Alpha	0.01	0.41	-0.15	0.01	0.17
	No. of Factors	3.09	1.62	2	3	4
Sector	Adj R^2	0.60	0.26	0.44	0.67	0.81
	Alpha	0.02	0.50	-0.19	0.01	0.21
	No. of Factors	2.92	1.72	2	3	4
All Funds	Adj R^2	0.58	0.26	0.40	0.63	0.79
	Alpha	0.02	1.14	-0.14	0.01	0.17
	No. of Factors	2.80	1.65	2	3	4

Table 3: Factor Model Exposure and T-Stat
This table reports the summary statistics of the top five factors selected in the step wise regression. The sample data used span from January 1994 to December 2013.

Variable	# Selected	Mean Exposure	Hit Rate	#T-Stat>1.96	# T-Stat>2.33	Mean T-Stat
MSCI EAFE	89,321	0.627	28%	85,420	79,596	4.80
Russell 3000	87,319	0.629	27%	84,106	79,287	5.65
SMB	71,466	0.507	22%	64,573	54,455	3.58
UMD	62,493	0.002	20%	55,906	44,607	3.48
HML	59,617	-0.101	19%	53,599	44,607	3.49

Table 4: Univariate Portfolio Sort: R-Square and Tail Risk

This table reports estimated tail risk based on 24 month rolling observations for different R-square quintiles estimated from step wise regression. The sample data used span from January 1994 to December 2013.

Portfolio	Adj. R^2	Tail risk	Hit Rate	T-Stat of Tail risk Quintile Difference	
1(Lowest)	0.18	3.93	51.90%		
2	0.45	0.60	43.24%	diff = mean(1) - mean(2)	t = 4.89***
3	0.62	0.64	35.68%	diff = mean(2) - mean(3)	t = -0.86
4	0.76	0.52	28.57%	diff = mean(3) - mean(4)	t = 1.09
5(Highest)	0.89	0.52	17.70%	diff = mean(4) - mean(5)	t = -0.03
1-5		3.41 (5.83)***	35.52%		

Table 5: Univariate Analysis-Hedge Fund Characteristics
This table reports fund characteristics for low R-square, high R-square and full sample of hedge funds. It also reports the Q1-Q5 values and the statistical significance of the difference. The sample data used span from January 1994 to December 2013.

Variable	Low R^2 (Q1)	High R^2 (Q5)	All Funds	1-5	T-Stat
size	17.42	17.49	17.47	-0.07	-6.05***
Log(age)	4.10	4.38	4.22	-0.28	-81.18***
lockup	1.40	1.47	1.46	-0.07	-11.69***
No of nonlinear factors	0.27	0.99	0.64	-0.71	-170.00***
Residual kurtosis	3.27	3.05	3.07	0.22	25.54***
mfee	1.47	1.34	1.41	0.13	41.49***
ifee	18.51	16.71	17.97	1.80	51.39***
lev	0.61	0.56	0.59	0.04	12.02***
hwm	0.81	0.76	0.80	0.05	20.63***
offsh	0.58	0.46	0.53	0.12	43.57***
mininv	16.28	10.43	11.86	5.85	7.94***
Residual skewness	0.11	0.02	0.05	0.09	22.69***
Advanced Notice Days	40.46	36.11	39.03	4.34	24.40***

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Other Information: Prime Broker, Auditor and Administrator

This table reports the top six Prime Brokers, Auditors and Fund Administrators and % market share for low R^2 funds and how that compares with high R^2 funds. The sample data used span from January 1994 to December 2013.

	Low R^2	High R^2
Prime Broker	Morgan Stanley (9.34%)	Morgan Stanley (10.27%)
	Goldman Sachs (7.26%)	Goldman Sachs (7.19%)
	Goldman Sachs & Co (4.83%)	JP Morgan (3.67%)
	JP Morgan (3.22%)	UBS (3.55%)
	Bear Stearns Asset Management Inc (3%)	Bear Stearns Asset Management Inc (2.7%)
	UBS (2.57%)	Goldman Sachs & Co (2.69%)
Auditor	PricewaterhouseCoopers (10.83%)	Ernst & Young (8.55%)
	Ernst & Young (8.12%)	PricewaterhouseCoopers (8.34%)
	PricewaterhouseCoopers (Isle of Man) (6.8%)	KPMG (7.5%)
	KPMG (6.32%)	Ernst & Young Accountants (4.35%)
	Ernst & Young Accountants (5.51%)	Deloitte (4.09%)
	KPMG (Cape Town) (4.31%)	PricewaterhouseCoopers (Isle of Man) (3.11%)
Administrator	CITCO (2.97%)	CITCO (3.3%)
	Citco Fund Services (2.33%)	Northern Trust (1.76%)
	HSBC (1.81%)	UBS (1.66%)
	Goldman Sachs (1.43%)	Citco Fund Services (1.54%)
	Citi (1.36%)	Morgan Stanley Fund Services USA LLC (1.43%)
	HSBC (Hong Kong) (1.31%)	HSBC (1.37%)

Table 7: Low R-Square Funds: Style Concentration

This table reports the style concentration for low R^2 funds and tail risk for each of the hedge fund styles. The sample data used span from January 1994 to December 2013.

Style	Q1 - Style %	Q1 -Tail Risk	Q5 – Style %	Q5-Tail Risk
Event Driven	17.2%	3.44	9.4%	0.40
Emerging Market	7.4%	4.10	6.9%	0.81
Long Only	6.4%	6.47	9.0%	0.61
Long Short	53.5%	4.27	67.4%	0.52
Market Neutral	12.6%	1.85	2.3%	0.31
Short Bias	0.4%	0.39	2.0%	0.05
Sector	2.5%	4.63	3.1%	0.60

Table 8: Determinants of R-Square

This table reports regression coefficients and standard errors of linear regressions. In Model 1, I regress R-squareds on the following fund characteristics: log (AUM), which is the natural logarithm of the size of the fund, US$; log (Age), which is the length of time the fund has existed in the sample; Lockup is the lockup period for a fund combined with the redemption notice period. I use number of nonlinear factors and kurtosis of residual as independent variables. I also include tail risk, hedge fund characteristics and max return (trailing 24 month maximum returns) in Models 2, 3 and 4 respectively in that order. Model 5 has excluded size, log (Age), nonlinear factors, kurtosis and skewness from model 4 to examine how tail risk and max return explain fund R-square. The sample data used span from January 1994 to December 2013.

Clustered standard error by fund and time

	Mode1 1	Model 2	Model 3	Model 4	Model 5
Tail Risk		-0.006***	-0.005***	-0.005***	-0.007***
		[0.00]	[0.00]	[0.00]	[0.00]
Size	-0.002	-0.002	0.255	0.461***	
	[0.14]	[0.14]	[0.17]	[0.17]	
Log(age)	7.095***	7.089***	6.197***	6.373***	
	[0.37]	[0.37]	[0.47]	[0.47]	
lockup	0.281	0.28	0.837**	0.737**	1.047***
	[0.24]	[0.24]	[0.36]	[0.36]	[0.35]
No of nonlinear factors	10.477***	10.477***	10.794***	10.826***	
	[0.16]	[0.16]	[0.18]	[0.18]	
kurtosis of residual	-1.594***	-1.590***	-1.552***	-1.730***	
	[0.13]	[0.13]	[0.15]	[0.16]	
mfee			-1.16	-1.331	-2.141**
			[0.82]	[0.83]	[0.97]
ifee			-0.424***	-0.420***	-0.476***
			[0.08]	[0.08]	[0.07]
lev			-0.354	-0.425	-0.157
			[0.66]	[0.66]	[0.64]
hwm			0.521	0.612	0.427
			[0.86]	[0.85]	[0.81]
offsh			-3.601***	-3.620***	-4.120***
			[0.70]	[0.69]	[0.70]
mininv			-0.004	-0.005	0.007
			[0.01]	[0.01]	[0.01]
skewness of residual			-1.199***	-1.705***	
			[0.30]	[0.30]	
Advanced Notice Days			-0.035***	-0.033**	-0.039***
			[0.01]	[0.01]	[0.01]
Max return				26.043***	0.157
				[3.40]	[0.53]
constant	41.185***	41.197***	39.705***	33.007***	74.883***
	[3.62]	[3.62]	[4.67]	[4.75]	[3.59]
Adj R-square	0.172	0.172	0.201	0.209	0.062
Strategy dummies	Yes	Yes	Yes	Yes	Yes

Observations	252,274	252,274	163,996	163,996	195,670

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 9: Univariate Portfolio Sort: R-Square and Alpha
This table reports estimated 12 month forward alpha for different R-square quintiles estimated from step wise regression. The sample data used span from January 1994 to December 2013.

Portfolio	Adj. R^2	Alpha	T-Stat of Alpha Quintile Difference	
1 (Lowest)	0.18	7.17%		
2	0.45	4.78%	diff = mean(1) - mean(2)	t = 3.38***
3	0.62	2.31%	diff = mean(2) - mean(3)	t = 4.50***
4	0.76	1.35%	diff = mean(3) - mean(4)	t = 2.00**
5(Highest)	0.89	0.39%	diff = mean(4) - mean(5)	t = 2.04**
1-5		6.78%		
		(10.02)***		

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10: Conditional Sort – R-Square and Re-estimated R-Square

This table reports the re-estimated adjusted R-square from the stepwise regression after including tail risk factor conditioned on previously estimated R-square quintiles. The sample data used span from January 1994 to December 2013.

Portfolio	Adj. R^2	Re-estimated Adj. R^2	Abs Increase in Adj. R^2	% increase in Adj. R^2
1 (Lowest)	17.76%	19.94%	2.18%	12.29%
2	45.10%	47.31%	2.21%	4.91%
3	62.30%	63.87%	1.57%	2.52%
4	76.03%	76.80%	0.77%	1.01%
5(Highest)	89.39%	89.29%	-0.10%	-0.11%
Average	58.11%	59.66%	1.55%	2.66%

Table 11: Low R^2 Fund Transitions

This table reports the proportion of low R^2 funds (estimated from the stepwise regressions) that remain low R^2 funds (estimated from stepwise regressions after taking into account systematic tail risk). The sample data used span from January 1994 to December 2013.

Quintile	% of Funds
Q1 (old) -> Q1 (new)	93.8%
Q1 (old) -> Q2 (new)	4.3%
Q1 (old) -> Q3 (new)	1.4%
Q1 (old) -> Q4 (new)	0.4%
Q1 (old) -> Q5 (new)	0.1%

Table 12: Conditional Sort – R-Square and Re-estimated Alpha

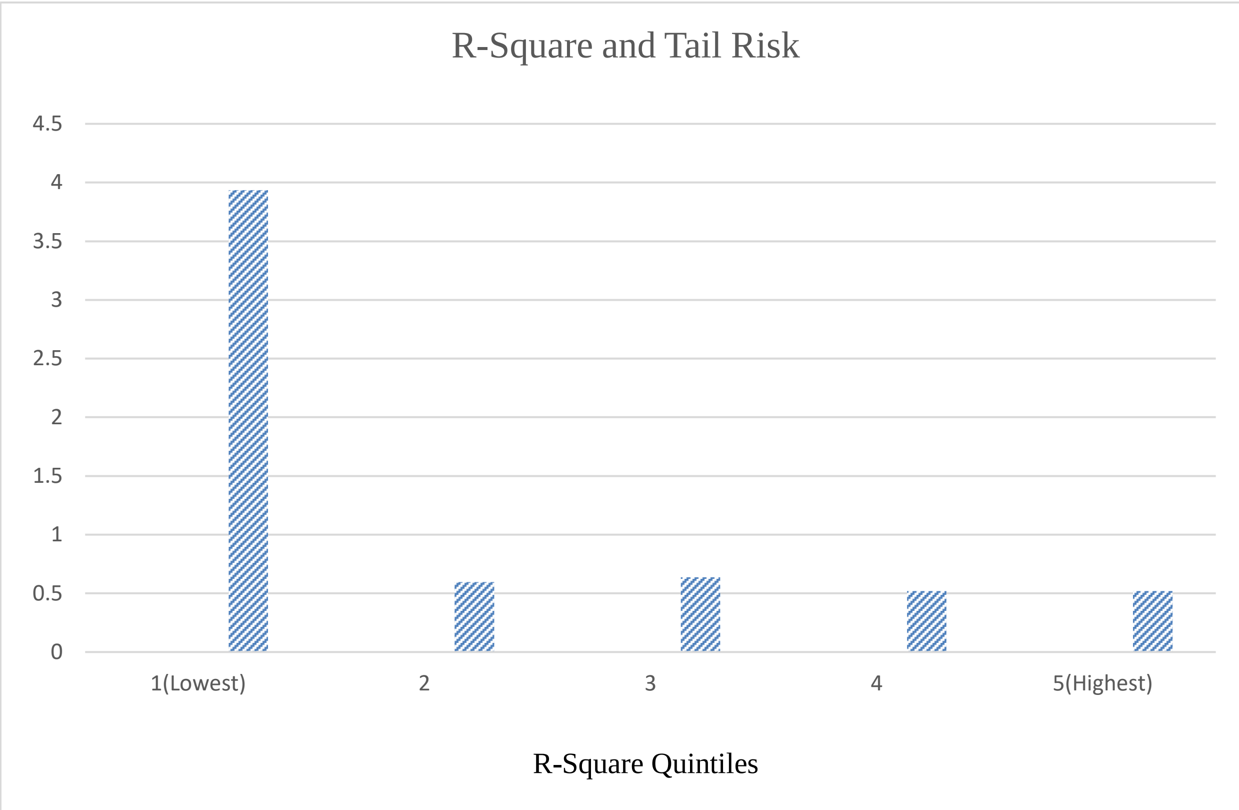
This table reports the re-estimated 12 month forward alpha from the stepwise regression after including tail risk factor conditioned on previously estimated R-square quintiles and compares it with previously estimated 12 month forward alpha values. The sample data used span from January 1994 to December 2013.

Portfolio	Alpha	Re-estimated Alpha	Decrease in Q1-Q5 Alpha spread	% Decrease	Tail Risk Avg. Exposure	Tail Risk Avg. T-Stat
1 (Lowest)	7.17%	6.66%			0.096	4.46***
2	4.78%	5.54%			-0.028	4.09***
3	2.31%	2.51%			-0.076	4.56***
4	1.35%	3.04%			-0.086	4.75***
5(Highest)	0.39%	0.45%			-0.002	4.81***
1-5	6.78%	6.21%	0.57%	8.4%		
	(10.02)***	(6.47)***				

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Appendix B Exhibits

Exhibit 1. R-Square and Tail risk



REFERENCES

Agarwal, Vikas, and Narayan Y. Naik,2000, Generalized style analysis of hedge funds, *Journal of Asset Management* 1(1), 93–109.

Agarwal, Vikas, and Narayan Y. Naik, 2000, On taking the alternative route: risks, rewards, and performance persistence of hedge funds, *Journal of Alternative Investments* 2, 6–18.

Agarwal, Vikas, and Narayan Y. Naik, 2004, Risks and portfolio decisions involving hedge funds, *Review of Financial Studies* 17, 63–98.

Agarwal, V.; V. Fos; and W. Jiang. “Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings.” Management Science, forthcoming (2013).

Agarwal, Vikas, Gurdip Bakshi, and Joop Huij, 2009, Do higher-moment equity risks explain hedge fund returns? Working Paper, Erasmus University, Georgia State University, and University of Maryland.

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik, 2011,” Do hedge funds manage their reported returns?” Review of Financial Studies 24, 3282-3320.

Agarwal, Vikas, Gerald D. Gay, and Leng Ling. "Window dressing in mutual funds." Review of Financial Studies (2014): hhu045.

Agarwal, Vikas, Naveen Daniel, and Narayan Naik, 2009, the role of managerial incentives and discretion in hedge fund performance, Journal of Finance 44, 2221–2256.

Agarwal, Vikas, Yakup E. Arisoy, and Narayan Y. Naik, 2016, Volatility of aggregate volatility and hedge fund returns, Working Paper, Georgia State University, London Business School, and University of Paris Dauphine.

Agarwal, Vikas and Ruenzi, Stefan and Weigert, Florian, Tail Risk in Hedge Funds: A Unique View from Portfolio Holdings (August 10, 2016). Journal of Financial Economics (JFE), Forthcoming.

Agarwal, V.; W. Fung; Y. Loon; and N. Naik. "Risk and Return in Convertible Arbitrage: Evidence from the Convertible Bond Market." Journal of Empirical Finance, 18 (2011), 175–194.

Amihud, Y., & Goyenko, R. (2013). Mutual Fund's R^2 as Predictor of Performance. *Review Of Financial Studies*, *26*(3), 667-694.

Aragon, George O., 2007, Share restrictions and asset pricing: Evidence from the hedge fund industry, Journal of Financial Economics 83, 33–58.

Bali, Turan G., Stephen J. Brown, and Mustafa O. Caglayan, 2014, Macroeconomic risk and hedge fund returns, *Journal of Financial Economics* 114, 1–19.

Bali, T.; S. Brown; and M. Caglayan. "Systematic Risk and the Cross Section of Hedge Fund Returns." Journal of Financial Economics, 106 (2012), 114–131

Bali, Turan G. and Brown, Stephen and Caglayan, Mustafa Onur, Upside Potential of Hedge Funds as a Predictor of Future Performance (October 23, 2017). Georgetown McDonough School of Business Research Paper No. 2661752.

Berk, J., Green, R., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269–1295.

Bollen, Nicolas P. B., 2013, Zero-R^2 hedge funds and market neutrality, *Journal of Financial and Quantitative Analysis*, 48(2), 519–547.

Bollen, N., and V. Pool. "Do Hedge Fund Managers Misreport Returns? Evidence from the Pooled Distribution." Journal of Finance, 64 (2009), 2257–2288.

Bollen, Nicolas P.B., and Robert E. Whaley, 2009, Hedge fund risk dynamics: Implications for performance appraisal, *Journal of Finance* 64, 985–1035.

Bondarenko, Oleg, 2004, Market price of variance risk and performance of hedge funds, Working Paper, University of Illinois.

Brands, S.Brown, S. J., and D.R.Gallagher. 2006. Portfolio concentration and investment manager performance. International Review of Finance 5:149–74.

Brown, Stephen J., William Goetzmann, and James Park, 2001, Careers and survival: Competition and risk in the hedge fund and CTA industry, Journal of Finance, 56(5), 1869–1886.

Buraschi, Andrea, Robert Kosowski, and Fabio Trojani, 2014, When there is no place to hide: Correlation risk and the cross-section of hedge fund returns, *Review of Financial Studies* 27, 581–616.

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

Cassar, G., and J. Gerakos. “Hedge Funds: Pricing Controls and the Smoothing of Self-Reported Returns.” Review of Financial Studies, 24 (2011), 1698–1734.

Cremers,M., and A. Petajisto. 2009.How active is your fundmanager?A new measure that predicts performance. Review of Financial Studies 22:3329–65.

Cremers,M.,M. Ferreira, P.Matos, and L. Starks. 2011. Themutual fund industry worldwide: Explicit and closet indexing, fees, and performance.Working Paper

Cremers, Martijn, Michael Halling, and David Weinbaum, 2015, Aggregate jump and volatility risk in the cross-section of stock returns, *Journal of Finance* 70, 577–614.

Duarte, J.; F. Longstaff; and F. Yu. “Risk and Return in Fixed Income Arbitrage: Nickels in Front of a Steamroller?” Review of Financial Studies, 20 (2007), 769–811.

Fama, Eugene F., and Kenneth R. French. "Common risk factors in the returns on stocks and bonds." Journal of financial economics 33.1 (1993): 3-56.

Fung, William, and David A. Hsieh, 1997, Empirical characteristics of dynamic trading strategies: The case of hedge funds, *Review of Financial Studies* 10, 275–302.

Fung, William, and David A. Hsieh, 2001, The risk in hedge fund strategies: Theory and evidence from trend followers, *Review of Financial Studies* 14, 314–341.

Fung, William, and David A. Hsieh, 2004, Hedge fund benchmarks: A risk-based approach, *Financial Analyst Journal* 60, 65–81.

Gao, George P., Pengjie Gao, and Zhaogang Song, 2014, Do hedge funds exploit rare disaster concerns?, Working Paper, Cornell University and the University of Notre Dame.

Getmansky, M.; A. Lo; and I. Makarov. “An Econometric Model of Serial Correlation and Illiquidity in Hedge Fund Returns.” Journal of Financial Economics, 74 (2004), 529–609.

Goetzmann, William N. and Ibbotson, Roger G. and Brown, Stephen J., Offshore Hedge Funds: Survival & Performance 1989-1995 (Undated). Yale School of Management Working Paper No. F-52B.

Glode, V., & Green, R. C. (2011). Information spillovers and performance persistence for hedge funds. Journal Of Financial Economics, 1011-17.

Kacperczyk,M. T., C. Sialm, and L. Zheng. 2005. On industry concentration of actively managed equity mutual funds. Journal of Finance 60:1983–2011.

Patton, Andrew J.. and Tarun Ramadorai, 2013, On the high-frequency dynamics of hedge fund risk exposures, *Journal of Finance* 68, 597–635.

Sadka, Ronnie, 2010, Liquidity risk and the cross-section of hedge fund returns, Journal of Financial Economics 98, 54–71.

Sharpe, William F., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Sharpe, William F., 1992, Asset allocation: Management style and performance measurement, *Journal of Portfolio Management*, 7–19.

Sun, Zheng, Ashley Wang, and Lu Zheng, 2012, The road less traveled: Strategy distinctiveness and hedge fund performance, *Review of Financial Studies*, 25(1), 96–143.

Teo, Melvyn, 2011, The liquidity risk of liquid hedge funds, Journal of Financial Economics 100, 24–44.

Titman, Sheridan, and Cristian Tiu, 2011, Do the best hedge funds hedge? *Review of Financial Studies* 24(1), 123–168.

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