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Zero-R^2 Hedge Funds and Market Neutrality

Nicolas P. B. Bollen*

Abstract

Factor models yield an R^2 insignificantly different from 0 for one-third of hedge funds in a broad sample. These funds illustrate the concept of market neutrality and feature lower volatilities, higher Sharpe ratios, and higher alphas than other funds, indicating that they provide a successful alternative investment. However, large portfolios of zero-R^2 funds contain fully half the volatility of portfolios of other funds, suggesting that they feature substantial systematic risk. Furthermore, these funds display an increased probability of failure even after controlling for idiosyncratic volatility. These results indicate the presence of an omitted factor that exposes investors to significant downside risk.

I. Introduction

Prior to the financial crisis, hedge funds were regarded as offering primarily upside risk given their remarkable performance. In response, investor capital flow fueled a 4-fold increase in aggregate assets under management between 1995 and 2007 to almost $2 trillion. Academic research also flourished, with a new strand of literature devoted to modeling the strategies employed by managers to deliver their superior returns. The aura surrounding the industry failed to survive 2008, however, when hedge funds returned –19% as measured by the Credit Suisse/Tremont Hedge Fund Index. Investors submitted a flood of withdrawal requests and voiced renewed interest in understanding how fund returns are generated and the nature of associated risks. From an academic perspective, it seems an appropriate time to assess the ability of existing research to provide insight regarding the risk and return trade-off in hedge funds.

Hedge funds are structured to satisfy exemptions from the Securities and Exchange Commission's (SEC) Investment Company Act and, in contrast to

*Bollen, nick.bollen@owen.vanderbilt.edu, Owen Graduate School of Management, Vanderbilt University, 401 21st Ave S, Nashville, TN 37203. I thank Stephen Brown (the editor), Bing Liang (the referee), Jacob Sagi, Mark Seasholes, and seminar participants at the University of Hong Kong, Hong Kong University of Science and Technology, Nanyang Technological University, National University of Singapore, Singapore Management University, and Vanderbilt University for their comments. Discussants at the 2011 Conference on Professional Asset Management (Rotterdam) and 2011 Conference on Hedge Funds (Paris) provided useful feedback. The Financial Markets Research Center at Vanderbilt University supplied generous support.

mutual funds, are not required to disclose their portfolio holdings.[1] Consequently, empirical studies of hedge fund performance generally rely on time-series regression analysis of monthly hedge fund returns, which many managers voluntarily report to one or more commercial databases.[2] Fung and Hsieh (1997) document the failure of standard factor model regressions to explain hedge fund returns, and they attribute the low explanatory power to several features of hedge funds, including dynamic strategies and positions in exotic securities, that are not captured by traditional buy-and-hold risk factors.

One approach to increase the explanatory power of hedge fund regression models is to develop style factors that mimic the time-series properties of various trading strategies. While these proxies are not priced risk factors, they can help identify which assets and strategies a particular fund employs, and they can establish a benchmark return to gauge the relative performance of individual funds in the spirit of Sharpe (1992). Fung and Hsieh (2001), for example, construct options-based factors to model the returns of trend-following funds. These factors can capture time-varying exposure to a variety of underlying assets, including equities, commodities, and foreign currencies. Agarwal and Naik (2004), Duarte, Longstaff, and Yu (2007), Agarwal, Fung, Loon, and Naik (2011), and Buraschi, Kosowski, and Trojani (2010), among others, develop additional proxies to capture patterns in returns of other hedge fund styles. Bali, Brown, and Caglayan (2012) find a significant positive link between a composite loading on sets of style factors and the cross section of future hedge fund returns, indicating that style factors capture systematic risk exposure. Another way to boost the performance of hedge fund factor models is to allow factor loadings to change over time in an effort to accommodate switches in fund strategy. Bollen and Whaley (2009) and Patton and Ramadorai (2013) show that time-varying factor loadings can increase explanatory power, though the relatively short histories of hedge funds pose significant challenges.

Despite the important contributions of prior research, the explanatory power of hedge fund factor models, as measured by regression R^2, remains relatively low.[3] Titman and Tiu (2011), for example, report an average R^2 for individual funds of just 26% using the widely adopted Fung and Hsieh (2004) 7-factor model and 43% using a stepwise approach and a set of 31 factors.

Perhaps the inability to capture time variation in hedge fund returns is a natural consequence of an underlying goal: The hedge fund industry generally strives to provide clients with an "alternative" investment that features low correlation with standard asset classes. Indeed, market-neutral funds are explicitly defined by the statistical independence of their returns, and for these funds a low R^2 would

[1]Section 404 of the Dodd-Frank Wall Street Reform and Consumer Protection Act includes a requirement that hedge funds disclose to the SEC trading and investment positions upon examination. However, these records are to remain confidential.

[2]Some studies, for example, Griffin and Xu (2009) and Brunnermeier and Nagel (2004), use SEC 13F filings to track positions in equities. Since these reports list equity holdings only, are filed quarterly, and provide limited information regarding short positions, they are inadequate for inferring the trading strategies and performance of a broad sample of hedge funds.

[3]In this paper, R^2 indicates a regression's adjusted R^2 unless stated otherwise.

be expected.[4] In an analysis of the determinants of R^2, Titman and Tiu (2011) find a negative relation between R^2 and fund fees, suggesting that investors are willing to pay more for funds with lower levels of systematic risk. Titman and Tiu treat a low R^2 as a signal of potential managerial skill and activity, and they show that funds with a low R^2 subsequently generate superior returns. Similarly, Sun, Wang, and Zheng (2012) find that funds featuring low correlation with other funds in the same style category demonstrate superior performance.[5] The results in Sun et al. (2012) and Titman and Tiu (2011) suggest that the low R^2 often found in hedge fund regression models indicates many fund managers are succeeding in offering an alternative, perhaps by engaging in differentiated trading styles or identifying arbitrage opportunities.

Although a low R^2 might be evidence of a successful alternative investment, there are two reasons why low-R^2 funds may expose investors to important and nondiversifiable risks.

First, a low R^2 indicates that a fund features relatively low levels of systematic risk but relatively high levels of idiosyncratic risk. High levels of idiosyncratic risk may result from a concentrated portfolio. Anecdotal evidence suggests that many fund managers take large positions in a small number of securities at any one time in an effort to exploit apparent mispricing. The resulting concentrated portfolio may increase the probability of a bad outcome simply through a lack of diversification. Alternatively, high levels of idiosyncratic risk may result from the pursuit of arbitrage opportunities. As argued by Pontiff (1996), (2006), idiosyncratic risk is the most important cost borne by arbitrageurs as they hold positions waiting for prices to converge. The resulting probability of short-term losses drives Shleifer and Vishny's (1997) limits to arbitrage theory of market inefficiency.

Second, despite the continued innovations of academic research, there will always remain the possibility that low-R^2 funds are exposed to one or more relevant risk factors that are omitted from the analysis. 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.

The goal of this paper is to characterize the risk profile of low-R^2 funds, taking into account the problems associated with the available hedge fund return data. I make three primary contributions.

First, I use a simulation-based technique to establish critical values for R^2 under the null hypothesis that fund returns are unrelated to 2 sets of factors gathered from prior research: the Fung and Hsieh (2004) 7-factor model and an extended 14-factor model that includes the Pástor and Stambaugh (2003) liquidity factor and the Agarwal and Naik (2004) index put option factor. Each fund

[4]Patton (2009) develops a number of different concepts of market neutrality and associated statistical tests. He finds that ¼ of market-neutral funds have statistically significant exposure to the Standard & Poor's (S&P) 500 index.

[5]Cremers and Petajisto (2009) study similar issues in mutual funds: They develop Active Share to measure the fraction of a fund's portfolio that is different from a benchmark index, and they show that it is correlated with fund performance.

is then placed into 1 of 2 distinct groups depending on whether the fund's actual R^2 exceeds the 95th percentile critical value. Funds that fail to reject the null are hereafter referred to as "zero-R^2" funds, for which R^2 is effectively 0. Using data on a broad cross section of funds from 1994–2008, I find that over ⅓ of all funds feature an R^2 insignificantly different from 0. The zero-R^2 phenomenon is especially pronounced in funds with short histories: Over 50% of funds with fewer than 36 observations fail to reject the null that their returns are random. I conduct several robustness tests, including dropping the first 18 observations of each fund to account for backfill bias, reversing the impact of serial correlation to account for smoothness, and allowing factor exposures to switch to account for the dynamic nature of hedge fund investment. In all cases, the percentage of zero-R^2 funds is quite similar. My results suggest that the ability to learn about a fund manager's trading style and selection of assets through the use of hedge fund regression models may be even weaker than the level of R^2 would indicate.

Second, I show that zero-R^2 funds in aggregate expose investors to ½ the systematic risk of other funds. I study the relative levels of idiosyncratic and systematic risk by forming random portfolios of zero-R^2 funds and measuring the relation between portfolio size and portfolio volatility. If the zero-R^2 funds offer purely idiosyncratic returns, then portfolio risk should be substantially reduced as the number of funds increases. I find that portfolios of 50 zero-R^2 funds feature fully ½ the volatility of portfolios constructed from other funds, suggesting substantial exposure to one or more omitted factors responsible for the comovement of zero-R^2 funds.[6]

Third, I show that the property of zero R^2 is a statistically and economically significant determinant of fund failure. I focus on fund failures because returns-based measures of downside risk can be misleading given the potential for return smoothing and the censoring of bad outcomes that occurs when a manager decides to stop reporting. In a proportional hazard rate model, I find that the marginal effect of a zero R^2 raises the unconditional annual probability of failure from 10% to 12%. The relation between a zero R^2 and fund failure is more pronounced in young funds; skillful managers that generate zero R^2 by focusing on arbitrage opportunities and exploiting mispriced securities are more likely to survive. More importantly, the impact of an insignificant R^2 on the probability of failure is robust to controlling for the level of idiosyncratic volatility estimated from each fund's factor model regression. This result indicates that the elevated failure rate of zero-R^2 funds is likely due to their exposure to omitted factors.

My results provide a means of reconciling contradictory evidence regarding hedge fund performance reported in prior studies. Some find significant abnormal hedge fund returns. Kosowski, Naik, and Teo (2007), for example, report strong evidence of superior performance in top funds using a bootstrap approach to control for luck and data limitations. Sorting on Bayesian performance measures yields striking evidence of predictability in hedge fund returns. Similarly, Jagannathan, Malakhov, and Novikov (2010) find that top-performing funds feature substantial persistence using nonoverlapping 3-year measurement windows.

[6]Brown, Gregoriou, and Pascalau (2011) find that the benefit of diversifying across hedge funds diminishes when the number of funds in a portfolio exceeds 20.

Several recent studies, however, find little evidence of abnormal performance. Griffin and Xu (2009), for example, use SEC 13F filings to assess the effectiveness of hedge fund trading activity while avoiding biases that arise in the voluntarily reported returns of commercial databases. They find scant evidence of stock picking ability and little differential performance across funds. My results indicate that factor models fail to measure systematic risk in over ½ of funds in commercial databases. These zero-R^2 funds appear to feature substantial exposure to an omitted systematic risk factor, so that prior evidence of abnormal risk-adjusted returns may be an upward-biased estimate of fund performance.

The rest of the paper is organized as follows: Section II reviews prior literature related to the R^2 of hedge fund factor models. Section III describes the data. Section IV explains the simulation methodology for determining critical values for R^2, followed by a presentation of summary statistics and main results in Section V. Section VI concludes with final remarks.

II. Interpreting R^2

A. R^2 for Hedge Funds

Hedge funds are known as alternative investments because they provide investors with exposure to assets and strategies that differ from the norm. Consequently, standard factor models fail to capture much of the time-series variation in hedge fund returns, as reflected in low R^2, motivating prior hedge fund research to develop new style factors in an effort to improve model fit. Fung and Hsieh (2001), for example, propose a new type of factor to represent the payoffs of trend-following strategies in various asset classes. A set of 5 trend-following factors achieves an R^2 of 47.9% in a regression with a portfolio of funds as the regressand, compared to an R^2 of 1.0% when the regressors are a set of 8 buy-and-hold factors involving standard assets such as equities, bonds, and commodities. This result suggests that new factors constructed to mimic hedge fund trading strategies may successfully capture the risks of hedge funds.

The performance of factor models can also be improved by explicitly allowing exposure to factors to vary over time to allow for changes in hedge fund strategy. Fung and Hsieh (2004) search for structural breaks in fund indices to identify industry-wide shifts in exposure, concluding that the Long-Term Capital Management (LTCM) collapse in Sept. 1998 and the peak of the technology bubble in March 2000 serve as useful common break points. These are also used in Fung, Hsieh, Naik, and Ramadorai (2008) in a study measuring performance of funds-of-funds. Similarly, Bollen and Whaley (2009) study the performance of a stochastic beta model and a switchpoint framework that allows discrete shifts in exposure and provide evidence supporting the latter. The average R^2 of funds with significant switches increases by more than ½, from 27.5% to 43.8%, when factor exposures are allowed to switch once.

Despite the efforts of prior research, there may be a limit to the explanatory power of hedge fund factor models given the expectations for managerial activity in hedge funds. High levels of residual volatility could stem from the pursuit of arbitrage opportunities, which by definition are orthogonal to factor returns,

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or from a portfolio that is concentrated in a relatively low number of securities. Furthermore, some managers develop new strategies in an effort to stay ahead of the pack, as copycat funds exhaust the potential for abnormal returns in previously used trading styles. A low R^2 can therefore be interpreted as a measure of the level of active management in a hedge fund.

Several studies use the degree of idiosyncrasy in a hedge fund's returns as a measure of managerial activity and skill. Sun et al. (2012), for example, argue that managers with skill and informational advantages likely pursue profitable trading strategies that are different from those followed by other managers; hence, low correlation with funds in the same category could be a predictor of abnormal performance. They find the difference between the subsequent 1-year returns of top and bottom quintiles of funds sorted by their strategy distinctiveness index, which equals 1 minus the correlation between a fund's returns and the average returns of funds in the same category, equals over 6%. Similarly, Titman and Tiu (2011) argue that skilled managers can better demonstrate their abilities, and justify their fees, by reducing exposure to systematic factors. Skilled managers of market-neutral funds, for example, can hedge beta risk to leverage a portfolio's long and short positions and maximize fund performance. Titman and Tiu find empirical support for an inverse relation between skill and R^2: Hedge funds in the lowest quartile, as ranked by adjusted R^2 of factor model regressions, tend to have the highest subsequent Sharpe ratios. These results suggest that funds with returns that are less correlated with other funds and with common style factors are more likely to be run by skilled managers.

B. R^2 and Hedge Fund Failure

While a low R^2 is consistent with the goal of generating abnormal returns, there are several reasons why a low R^2 may also indicate an elevated downside risk. In the empirical analysis relating R^2 to fund outcomes, I focus on fund failures because returns-based measures of performance can be misleading. Returns may be subject to smoothing, as in Getmansky, Lo, and Makarov (2004), who show that discretionary valuation of illiquid assets can result in artificially low volatility. Returns may be subject to misreporting. Bollen and Pool (2009) and Cassar and Gerakos (2011), for example, find that funds with illiquid assets feature an unusually low number of negative returns. As shown by Agarwal, Fos, and Jiang (2013), returns may be subject to censoring. When a manager suspects that future returns will be weak, he may decide to stop reporting to avoid publicly revealing poor performance. In contrast to returns-based measures of bad outcomes, fund failure is a less ambiguous signal of poor subsequent performance.

Funds with low R^2 could pose an elevated risk of failure if they consist of highly concentrated portfolios, which feature low levels of systematic risk, high levels of idiosyncratic risk, and a relatively high probability of an extreme outcome.[7] Alternatively, funds that eliminate or reduce factor exposure through

[7]Concentrated portfolios will likely feature more concentrated factor exposures. Indeed, I find that for low-R^2 funds, the most important factor accounts for 89% of a fund's systematic volatility, compared to 83% for other funds.

offsetting long and short positions, constituting a convergence bet, run the risk that the positions diverge instead. A classic example is LTCM's wager that the spread between the yields on U.S. and Russian government debt would converge. Convergence bets are also prone to the risk of abrupt changes in correlation between each position and underlying risk factors. As detailed in Buraschi et al. (2010), a strategy involving simultaneous long and short positions can sour due to abrupt changes in correlation, which typically occur during market downturns. Spikes in correlation can lead to an increased probability of fund failure when a fund's exposure to systematic risk factors increases at the wrong time. Brown et al. (2011) study portfolios of hedge funds and argue that diversifying across funds has the unintended result of magnifying the left tail, perhaps the result of correlation risk.

I test for a relation between low R^2 and increased failure rates using a proportional hazard rate model, controlling for other known determinants of fund failure, as well as annual fixed effects to capture time-series variation in failure rates caused by the market dependence described by Buraschi et al. (2010).

III. Data

The hedge fund data are drawn from the Center for International Securities and Derivatives Markets (CISDM) and the Lipper TASS (TASS) databases with observations from Jan. 1994 through Dec. 2008. Returns are net of all management and performance-based fees. Some fund managers report returns to both databases, and I carefully combine the databases to avoid duplications. Potential pairs of duplicated funds are identified by examining the names of funds in the 2 databases using a text-based matching algorithm. To verify matches, I then compute the correlation between the return series of the 2 funds in each pair. Pairs with correlation above 99% are deemed matches, and the series with the shorter history is discarded. Appendix A shows how I consolidate the style categories of the 2 databases.

Hedge fund managers voluntarily self-report returns of their funds, resulting in three important database issues. First, survivorship bias is generated when a database excludes funds that failed prior to the construction of the database, or eliminates failed funds from the database thereafter. Both the CISDM and TASS databases include failed funds, so survivorship bias is not a concern.

Second, backfill bias arises when a fund manager is able to report a past history of returns when joining a database. A manager is more likely to backfill returns following a period of superior performance; hence, returns are likely to be biased upward in the early stage of a hedge fund's reported history. A similar issue with the "incubation" of mutual funds is analyzed by Evans (2010). The purpose of my study is to measure the ability of factor models to capture time-series variation in observed fund returns, so in most of the analysis I include the full history of each fund. I ensure that the results are not dependent on backfilled returns in a robustness test that drops the first 18 months of each fund's history.

Third, censorship bias is caused by the decision of a manager to stop reporting returns while the fund is still a going concern. This is especially important for my study, because I use the end of a reporting history to proxy for fund failure.

However, as discussed by Ackermann, McEnally, and Ravenscraft (1999), Liang and Park (2010), and Jagannathan et al. (2010), a fund manager may decide to stop reporting for a number of reasons, including cases in which a fund experiences great success and reaches maximum capacity. A manager may also opt to cease reporting in anticipation of poor subsequent performance. The TASS database includes a field that indicates the reason for an end to a fund's history, but it is not available for all funds. Jagannathan et al. develop a statistical model that estimates conditional probabilities of the different reasons why a manager stopped reporting. I follow the approach advocated by Liang and Park, who argue that using a performance filter is a superior way to segregate true failures from funds that stop reporting for other reasons. Consequently, I consider a fund to fail if it ceased reporting prior to Dec. 2008, and if the fund's cumulative 12-month return computed on the last reporting date fell below the median of all funds in existence over that time period.

In addition to the 3 biases discussed previously, hedge fund returns often display serial correlation that is unobserved in underlying risk factors. As discussed in Getmansky et al. (2004), serial correlation can result from illiquidity in some fund assets, so that fund net asset values (NAVs) only slowly respond to new information. The Getmansky et al. model observed returns as moving averages of contemporaneous and lagged true portfolio returns, and they show how the moving average affects various statistical properties of fund returns, notably reducing exposures to underlying risk factors and the fund's R^2. I conduct a robustness test that repeats some of the analysis after reversing the impact of a moving average reporting algorithm.

I use 2 sets of risk factors in my analysis. Most of the reported results are derived from the 7-factor model of Fung and Hsieh (2004). These factors are drawn from 3 sources. The excess return of the market and the return of the size factor are from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). Three trend-following factors, which are the returns of portfolios of options on bonds, commodities, and exchange rates, are obtained from David Hsieh's Web site (https://faculty.fuqua.duke.edu/∼dah7/).[8] The change in the yield of a 10-year Treasury note and the change in the credit spread, defined as the yield on 10-year BAA corporate bonds less the yield of a 10-year Treasury note, are obtained from the St. Louis Federal Reserve Bank's Web site (http://research.stlouisfed.org/fred2/). To estimate the factor model, I also require a risk-free rate, and for this I use the 1-month T-bill rate from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). I use a 14-factor model to assess the impact of additional factors on the results; the extended factor subset subsumes the 7-factor model and adds others from 4 sources. The returns of the value and momentum factors are from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The stock and interest rate trend-following factors are from David Hsieh's Web site (https://faculty.fuqua.duke.edu/∼dah7/). The liquidity factor from Pástor and Stambaugh (2003) is from Lubos Pástor's Web site

[8]The file containing the trend-following factors is found at https://faculty.fuqua.duke.edu/∼dah7/HFRFData.htm

(http://faculty.chicagobooth.edu/lubos.pastor/research/). The Agarwal and Naik (2004) out-of-the-money (OTM) and at-the-money (ATM) index put factors were provided by Vikas Agarwal.

The actively managed equity mutual fund data are extracted from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free U.S. Mutual Fund database with observations through Dec. 2007. Appendix B explains how I extracted the actively managed equity funds from the full database. CRSP provides an indicator for whether the fund is "live" or "dead" in the fund header.

IV. R^2 and Critical Values

The growing list of factors developed to analyze hedge fund returns leads to an estimation problem: The potential number of factors can exceed the number of available observations given the relatively short histories available for many funds. A common approach to handling this issue is to select a subset of factors for a given fund, often by a series of stepwise regressions, as in Liang (1999), Agarwal and Naik (2004), and Titman and Tiu (2011). In this paper I search all possible subsets to identify for each fund the subset of factors that maximizes the R^2 of a regression of monthly fund excess returns on factor returns. I limit the number of possible factors to 3, which is the median number found in Titman and Tiu.

While a search of possible factors is a necessity for short-history funds, this type of procedure increases the potential for a spurious relation between a hedge fund's returns and those of the factors. As discussed in Foster, Smith, and Whaley (1997), one can achieve a seemingly substantial R^2 even if the dependent variable is completely unrelated to the independent variables, especially when searching a set of regressors to maximize R^2. They show that the likelihood of a spurious R^2 is increasing in the number of potential regressors and decreasing in the length of the time series. The authors advocate using critical values for the R^2 that take into account the number of observations and regressors used in the regression, as well as the number of potential regressors that were considered.

Given the limited histories of many hedge funds and the growing number of possible risk factors, the possibility of spurious R^2 is a significant concern in my study. To address this issue, I construct critical values for R^2 by simulating data under the null to determine what R^2 I might expect by chance. This procedure is an example of the "reality check" described in White (2000) to guard against data snooping.[9] On each December beginning in 1995, I randomly generate series of returns drawn from a standard normal distribution with a variety of history lengths. Then, for each series, I choose the optimal subset of up to 3 factors to maximize the R^2 for the randomly generated data. Each regression uses the factor returns observed during the period defined by the date and history length. I repeat the procedure 1,000 times at each date and each history length: The percentiles of the resulting 1,000 R^2 serve as critical values. Funds with actual R^2 smaller than

[9]Similar applications in Bollen and Whaley (2009) and Patton and Ramadorai (2013) test for significant changes in hedge fund factor exposures.

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the 95th percentile using the randomly generated data fail to reject the null that returns are random.

To illustrate, I construct critical values on Dec. 2008 using history lengths of 24, 60, and 120 months. The results are displayed in Table 1. Panels A and B present critical values using the 7- and 14-factor models, respectively. Naturally, the extended set of 14 factors leads to higher critical values than the 7-factor model simply because there are more combinations to fit random patterns in returns. Using a 24-month history, for example, the 14-factor model yields a median R^2 of 25.9%, versus 13.2% for the 7-factor model. This result shows the drawback to using ever-expanding sets of factors: They increase the possibility of spurious results. Note also that the critical values are much lower for longer histories. For example, the medians of the 14- and 7-factor models drop to 4.6% and 2.6%, respectively, at a history length of 120 months. It is more difficult to fit a long random pattern than a short one. This result indicates the need to construct critical values that take into account history length.

TABLE 1

Critical Values

Listed are percentiles of R^2 from regressions of random returns on factors that proxy for hedge fund strategies. The regressand consists of draws from a standard normal variable. For each window length, 1,000 series are generated. For each series, the optimal subset of up to 3 factors is selected to maximize the regression R^2. Observation periods for the factors are equal to the window length indicated in the table and end on Dec. 2008 in all cases. In Panel A of Table 1, the 7-factor model includes: the market excess return; the size factor; the commodity, bond, and foreign exchange trend-following factors; the change in the 10-year Treasury yield; and the change in the spread between the 10-year Treasury yield and the yield on 10-year BAA corporate bonds. In Panel B, the 14-factor model includes the 7 factors listed above, plus the value and momentum factors, the stock and interest rate trend-following factors, the liquidity factor of Pástor and Stambaugh (2003), and the OTM and ATM index put factors from Agarwal and Naik (2004). Panels C and D give corresponding results when factor exposures are allowed to switch once during each random history.

	Percentile				
No. of Obs.	5th	25th	50th	75th	95th
Panel A. 7-Factor Model					
24	−1.0%	4.8%	13.2%	20.4%	34.8%
36	−0.7%	3.5%	8.3%	15.7%	24.5%
60	−0.2%	1.6%	4.0%	8.8%	14.7%
120	0.3%	1.2%	2.6%	4.0%	9.1%
Panel B. 14-Factor Model					
24	6.4%	16.5%	25.9%	32.9%	46.5%
36	4.2%	10.0%	15.4%	23.3%	31.3%
60	1.6%	5.4%	8.5%	11.7%	18.9%
120	0.5%	2.5%	4.6%	6.5%	12.8%
Panel C. 7-Factor Switching Model					
24	−8.0%	2.3%	13.5%	25.8%	48.0%
36	−1.4%	6.0%	14.7%	21.5%	33.3%
60	0.6%	4.4%	8.2%	14.8%	24.2%
120	1.9%	4.3%	6.1%	8.6%	13.2%
Panel D. 14-Factor Switching Model					
24	−0.3%	13.4%	22.6%	34.7%	50.4%
36	4.1%	18.0%	23.9%	31.5%	44.5%
60	3.9%	10.0%	15.6%	20.6%	30.9%
120	2.8%	5.9%	8.4%	11.4%	15.6%

In much of the empirical analysis to follow, I allow factor loadings to switch once during a fund's life, following the 2-step procedure in Bollen and Whaley (2009). The subset of factors for a given fund is selected in the 1st step, in which the factor subset is selected to maximize R^2 with fixed factor loadings. In the 2nd step, factor loadings are allowed to switch. The switch date is selected by again maximizing R^2 by searching over all possible switch dates, ensuring that there are at least 12 observations in each estimation period. I account for estimation error that might occur if a switch date is selected near the beginning or end of a fund's history by constructing a different set of critical values when factor loadings are allowed to switch. These critical values also allow switch dates to occur any time so long as there are at least 12 observations from the beginning or end of each random sample. Panels C and D of Table 1 display critical values using randomly generated normal returns and the 7- and 14-factor models, respectively. These simulations show that the possibility of spurious R^2 is somewhat higher than the fixed-loading case. Using the 7-factor model and a 24-month history, for example, the 95th percentile R^2 is 48.0% compared to 34.8% when using fixed loadings.

I ensure that the R^2 critical values are robust to the distribution of the random data in two ways. First, I conduct a series of bootstrap simulations using student t-distributions for random returns instead of standard normal, and varying the degrees of freedom to generate different levels of excess kurtosis typically found in hedge fund returns. Second, I construct critical values by drawing with replacement from the pooled distribution of all hedge fund returns reported over the 1994–2008 period. In both cases the critical values for the regression R^2 are almost identical to those using data generated from a standard normal distribution; hence, in the next section my results are based on the latter.[10]

V. Results

A. Summary Statistics

Table 2 lists R^2 for 10 groups of hedge funds sorted by their history length. Listed is the average R^2 achieved for the funds in each group and the percentage of funds for which the actual R^2 falls short of the critical value. Panel A gives results for the 7-factor model. When factor loadings are restricted to be constant, average R^2 is slightly higher for the shorter histories, 32.9% for funds between 24 and 35 months, for example, compared to 29.4% for funds greater than 132 months. However, funds with shorter histories also feature the highest critical values, so that I fail to reject the hypothesis that the true R^2 is 0 for 55.1% of the youngest funds.[11] Note that this age group is also the most populous, containing 1,608 funds in the sample of 6,687. For the longer histories, the majority of funds feature significant R^2 because the critical values drop substantially as shown in Table 1. Nevertheless, for 36.6% of the entire hedge fund sample, I fail to reject the hypothesis that R^2 equals 0. In other words, despite searching over the set of

[10]This result is consistent with Ali and Sharma (1996), who study regression F-tests, which are closely related to R^2, and find that F-tests are quite robust to nonnormality.

[11]As shown in Table 1, shorter histories feature higher critical values because it is easier to fit a shorter random pattern than a longer one. To ensure that the high rate of a zero R^2 in young funds is not simply a result of the higher critical values, I examine the relation between zero R^2 and fund failure in Section V.C. The link is stronger for young funds.

7 factors used in prior hedge fund research, I fail to learn anything from statistical analysis for over 1 in 3 funds.

TABLE 2

Critical R^2

Listed are the average R^2 and the percent of funds for which the R^2 is insignificantly different from 0. Funds are split by history length, in months, computed over the 1994–2008 period. For each fund, the optimal subset of up to 3 factors is selected to maximize the R^2. The significance of each fund's R^2 is assessed by simulated critical values. Panels A and B of Table 2 give results for the 7- and 14-factor models, respectively. "Constant" presents results when factor exposures are held constant over each fund's history. "Switching" allows exposures to switch once over each fund's history.

		Constant		Switching	
Age	No. of Funds	Avg. R^2	% Zero-R^2	Avg. R^2	% Zero-R^2
Panel A. 7-Factor Model					
$24 \leq t < 36$	1,608	32.9%	55.1%	39.7%	56.5%
$36 \leq t < 48$	1,164	31.6%	41.7%	41.3%	40.3%
$48 \leq t < 60$	858	29.5%	37.5%	40.6%	30.9%
$60 \leq t < 72$	698	30.4%	29.2%	41.6%	21.5%
$72 \leq t < 84$	542	29.4%	28.8%	40.2%	17.3%
$84 \leq t < 96$	438	27.1%	31.7%	38.0%	17.4%
$96 \leq t < 108$	313	28.6%	23.0%	40.1%	16.3%
$108 \leq t < 120$	257	28.0%	21.8%	40.8%	10.5%
$120 \leq t < 132$	171	26.4%	21.6%	38.2%	9.9%
$132 \leq t$	638	29.4%	13.8%	38.4%	7.2%
All funds	6,687	30.4%	36.6%	40.1%	31.4%
Panel B. 14-Factor Model					
$24 \leq t < 36$	1,608	43.6%	51.4%	50.2%	53.2%
$36 \leq t < 48$	1,164	40.2%	38.1%	49.1%	36.9%
$48 \leq t < 60$	858	37.2%	30.8%	47.4%	23.8%
$60 \leq t < 72$	698	36.8%	26.2%	46.9%	18.2%
$72 \leq t < 84$	542	36.0%	20.8%	46.0%	14.8%
$84 \leq t < 96$	438	33.5%	19.4%	43.7%	13.0%
$96 \leq t < 108$	313	34.3%	17.3%	45.2%	9.3%
$108 \leq t < 120$	257	33.1%	16.7%	45.2%	6.6%
$120 \leq t < 132$	171	31.2%	13.5%	42.0%	7.6%
$132 \leq t$	638	33.4%	9.9%	42.0%	4.1%
All funds	6,687	38.1%	31.4%	47.1%	27.5%

When factor loadings are allowed to switch, average R^2 improves for the full sample of funds from 30.4% in the constant loadings case to 40.1%, consistent with the results in Bollen and Whaley (2009). Furthermore, the percentage of funds with R^2 that fail to exceed the 95th percentile critical value drops from 36.6% to 31.4%. However, for the first 2 age groups, the percentage of zero-R^2 funds is essentially the same as before: 56.5% for the youngest funds, for example, compared to 55.1% when factor loadings are restricted to be constant.

Results are qualitatively similar for the 14-factor model displayed in Panel B of Table 2. The additional factors increase the average R^2 for the constant-loading and switching models to 38.1% and 47.1%, respectively, from 30.4% and 40.1% in Panel A, but also result in higher critical values, so that the percentage of zero-R^2 funds is roughly the same as before. As in Panel A, for both the constant-loading and switching models, for the youngest funds, over 50% fail to reject the null hypothesis that R^2 equals 0. In summary, for many funds, especially young funds, one in a sense can learn nothing from statistical analysis about how returns are generated. The relatively low R^2 achieved by prior research for hedge funds actually overstates one's understanding of the sources of hedge fund risk.

To examine the variation in model fit across styles, Table 3 gives the average R^2 and percentage of zero-R^2 funds for subsets based on style. The additional factors of the 14-factor model increase the average R^2 of all fund styles compared to the 7-factor model, so that the relative performance of the models across styles is fairly constant. Equity market-neutral and macro funds feature the lowest average R^2 in both models, for example, whereas single-strategy funds feature the highest average R^2 in both models. In both the 7- and 14-factor models, however, the R^2 averages for the largest 4 styles (equity, multistrategy, event driven, and emerging markets) are quite close, and all are substantially below 50%. This result illustrates that low R^2 is a general feature of hedge funds.

TABLE 3

Fund Styles

Listed for each style are the number of funds, average R^2, and the percent of funds for which the R^2 is insignificantly different from 0. Data are from the 1994–2008 period. Results are displayed for 2 sets of factors: a 7-factor model and a 14-factor model. For each fund, the optimal subset of up to 3 factors is selected to maximize the R^2. The significance of each fund's R^2 is assessed by simulated critical values.

		7-Factor Model		14-Factor Model	
Style	No. of Funds	Avg. R^2	% Zero-R^2	Avg. R^2	% Zero-R^2
Equity	2,890	33.2%	31.7%	41.6%	25.3%
Multistrategy	708	31.2%	37.0%	39.4%	31.1%
Event driven	550	31.7%	29.3%	37.2%	28.9%
Emerging markets	533	33.3%	25.0%	39.0%	25.5%
Equity market neutral	479	18.6%	62.8%	29.7%	45.5%
Fixed income	411	25.7%	48.7%	31.5%	46.5%
Macro	428	22.5%	50.5%	29.4%	47.2%
Convertible arbitrage	253	25.4%	45.8%	30.1%	46.6%
Sector	178	32.0%	31.5%	41.5%	28.7%
Other	80	24.2%	51.3%	32.0%	46.3%
Distressed securities	74	36.9%	23.0%	41.4%	18.9%
Short bias	55	33.6%	36.4%	40.1%	32.7%
Single strategy	48	47.3%	10.4%	53.5%	10.4%
Total	6,687	30.4%	36.6%	38.1%	31.4%

As noted in Section III, hedge fund return databases suffer from a number of shortcomings that may impact my analysis. I conduct 2 robustness tests to ensure that the conclusions are unaffected after correcting for well-known biases. Results of the robustness tests using the 7-factor model are displayed in Table 4.

First, I control for serial correlation in returns motivated by the model of smoothing in Getmansky et al. (2004). I identify funds for which the 1st-order serial correlation in returns is positive and significant at the 5% level. For these funds, I remove serial correlation following the procedure described in Appendix C before conducting the factor model regressions. With constant factor loadings, Panel A of Table 4 indicates that the average R^2 of the adjusted returns is slightly lower than when raw returns are used, 28.4% versus the 30.4% reported in Table 2, and the percentage of zero-R^2 funds is slightly higher, 38.7% versus 36.6%. Similar results hold with switches in factor loadings. The smoothing model predicts that R^2 should increase when serial correlation is removed from the data, so clearly my results are not driven by this phenomenon.

Second, I control for backfill by dropping the first 18 months of observations from each fund's history. Since managers can introduce a fund's history to

TABLE 4

Robustness Tests

Listed are the average R^2 and the percent of funds for which the R^2 is insignificantly different from 0 using a 7-factor model. Funds are split by history length, in months, computed over the 1994–2008 period. For each fund, the optimal subset of up to 3 factors is selected to maximize the R^2 using the 7-factor model. The significance of each fund's R^2 is assessed by simulated critical values. "Constant" gives results when factor exposures are held constant over each fund's history. "Switching" allows exposures to switch once over each fund's history. In Panel A of Table 4, returns of funds with statistically significant serial correlation are adjusted to remove the effect of smoothing. In Panel B, the first 18 observations of each fund are dropped to remove the effect of backfill.

		Constant		Switching	
Age	No. of Funds	Avg. R^2	% Zero-R^2	Avg. R^2	% Zero-R^2
Panel A. Control for Serial Correlation					
$24 \leq t < 36$	1,608	31.4%	56.5%	38.0%	59.6%
$36 \leq t < 48$	1,164	29.4%	43.9%	38.7%	43.6%
$48 \leq t < 60$	858	27.6%	39.5%	38.0%	35.1%
$60 \leq t < 72$	698	28.3%	30.8%	39.3%	23.6%
$72 \leq t < 84$	542	26.8%	31.0%	37.3%	19.6%
$84 \leq t < 96$	438	24.1%	35.2%	34.4%	21.5%
$96 \leq t < 108$	313	26.5%	25.9%	37.2%	19.5%
$108 \leq t < 120$	257	25.5%	23.3%	36.8%	12.5%
$120 \leq t < 132$	171	24.4%	24.0%	35.2%	11.1%
$132 \leq t$	638	27.7%	16.9%	36.0%	10.5%
All funds	6,687	28.4%	38.7%	37.6%	34.6%
Panel B. Control for Backfill					
$24 \leq t < 36$	945	36.2%	50.3%	42.9%	51.7%
$36 \leq t < 48$	790	32.2%	39.7%	41.7%	36.5%
$48 \leq t < 60$	618	34.5%	31.4%	44.0%	27.2%
$60 \leq t < 72$	510	31.3%	27.6%	41.0%	22.0%
$72 \leq t < 84$	367	29.8%	29.4%	40.4%	19.6%
$84 \leq t < 96$	305	31.5%	29.8%	42.7%	16.7%
$96 \leq t < 108$	217	29.2%	21.2%	39.3%	15.7%
$108 \leq t < 120$	163	28.9%	23.9%	40.7%	8.6%
$120 \leq t < 132$	140	28.6%	16.4%	39.5%	7.1%
$132 \leq t$	431	31.2%	11.1%	39.7%	8.4%
All funds	4,486	32.5%	33.0%	41.7%	28.4%

a database when first reporting, the early returns may differ from the norm and may be less correlated with factors than the regularly reported returns. Panel B of Table 4 gives the results. The number of funds with at least 24 observations drops substantially, from 6,687 to 4,486. The average R^2 and percentage of zero-R^2 funds are similar to the results in Table 2. Overall, the results in Table 4 indicate that my analysis is unaffected by well-known biases in hedge fund return data.

Table 5 gives summary statistics for subsets of funds. Panels A and B give results for subsets of hedge funds formed by whether the R^2 of a fund exceeds (Panel A) or falls short (Panel B) of the 95th percentile critical values using the 7-factor model. There are several pronounced differences. The average history length of funds in Panel A is substantially longer than the average of funds in Panel B, 75 months versus 54 months. This result has two possible causes. First, as shown in Table 2, shorter histories increase the critical values of R^2, making it more difficult to reject the null that the R^2 equals 0. Second, insignificant R^2 could be a determinant of fund failure (perhaps because the unknown strategy of the fund is in some sense riskier) so that surviving funds tend to have higher R^2. Zero-R^2 funds feature lower standard deviation than other funds, however, suggesting that if anything, the zero-R^2 funds have lower risk. Comparing across

Panels A and B, the zero-R^2 funds have standard deviation of 3.42% versus 4.65% for other funds.

TABLE 5

Summary Statistics of Fund Subsets

Listed are summary statistics of funds from the CISDM and TASS databases using monthly returns from 1994–2008. Only funds with at least 24 observations in this period are included. The summary statistics are the equal-weighted cross-sectional averages of the number of monthly observations; the mean monthly return, μ; the standard deviation of monthly returns, σ; the Sharpe ratio, *SR*; the skewness, *Skew*; the excess kurtosis, *Kurt*; the abnormal monthly return from the optimal factor model, α; the adjusted R^2 from the optimal factor model, R^2; and residual volatility from the optimal factor model, σ_ε. Results are split by whether the funds are live or defunct as of Dec. 2008, and they are also displayed for the combined sample. Panels A and B of Table 5 correspond to subsets formed by whether a fund's R^2 is significantly different from 0 using the 7-factor model. Significance is assessed using simulated critical values. Panels C and D correspond to subsets formed by whether a fund's R^2 is significantly different from 0 using the 14-factor model.

Type	No. of Funds	No. of Obs.	μ	σ	*SR*	*Skew*	*Kurt*	α	R^2	σ_ε
Panel A. Hedge Funds with 7-Factor Model $R^2 > 0$										
Live	2,615	80	0.0059	0.0452	0.0929	−0.7264	5.0611	0.49%	42.47%	0.0321
Defunct	1,627	67	0.0059	0.0486	0.0893	−0.4101	4.0148	0.15%	39.76%	0.0347
All	4,242	75	0.0059	0.0465	0.0915	−0.6051	4.6598	0.36%	41.43%	0.0331
Panel B. Hedge Funds with 7-Factor Model $R^2 = 0$										
Live	1,342	58	0.0097	0.0341	0.3368	0.1061	4.0873	0.74%	10.69%	0.0308
Defunct	1,103	48	0.0042	0.0344	0.0861	−0.1829	3.8836	0.11%	11.92%	0.0307
All	2,445	54	0.0072	0.0342	0.2237	−0.0243	3.9954	0.45%	11.24%	0.0308
Panel C. Hedge Funds with 14-Factor Model $R^2 > 0$										
Live	2,909	79	0.0062	0.0440	0.1045	−0.6801	5.0272	0.43%	47.09%	0.0297
Defunct	1,679	67	0.0058	0.0483	0.0850	−0.4065	3.9343	0.14%	46.03%	0.0324
All	4,588	75	0.0061	0.0456	0.0974	−0.5800	4.6272	0.32%	46.70%	0.0307
Panel D. Hedge Funds with 14-Factor Model $R^2 = 0$										
Live	1,048	54	0.0098	0.0344	0.3730	0.2111	3.9083	0.77%	18.94%	0.0293
Defunct	1,051	48	0.0042	0.0341	0.0927	−0.1774	4.0058	0.10%	19.40%	0.0289
All	2,099	51	0.0070	0.0343	0.2327	0.0166	3.9572	0.44%	19.17%	0.0291

The last 3 columns include statistics from each fund's optimal factor model. Consistent with the results of Titman and Tiu (2011), zero-R^2 funds achieve higher alphas. Live zero-R^2 funds, for example, have average monthly alpha of 0.74% compared to 0.49% for other live funds. Perhaps surprisingly, zero-R^2 funds feature lower average levels of idiosyncratic risk than other funds, 3.08% monthly versus 3.31%. I present alternative measures of systematic and idiosyncratic risk in the next subsection using a technique that avoids the need to identify sources of systematic risk. Panels C and D present corresponding summary statistics for funds using the 14-factor model. Results are qualitatively similar.

I measure differences in fund characteristics of the zero-R^2 funds compared to other funds in a multivariate setting using a probit analysis. The dependent variable equals 1 for zero-R^2 funds, and 0 otherwise. The independent variables include *Age*, fund age (in months) at the last reported monthly return; *Size*, fund size as measured by the natural logarithm of the maximum assets under management reached during the fund's life; *Equity*, an indicator variable that equals 1 for funds in the equity style, and 0 otherwise; *Kurt*, excess kurtosis; and *ES*, expected shortfall, defined as the expected return below a threshold. Liang and Park (2010) advocate a nonparametric threshold given by a fixed percentile of a fund's empirical distribution; I use the 5th percentile.[12] Results are displayed in Table 6. All determinants are significant at the 5% level except for fund size. This result suggests that some large funds are able to generate high levels of idiosyncratic risk (presumably through effective hedging of systematic risk factors). The probability of a zero R^2 is strongly decreasing with age, consistent with the results in Table 2, and substantially lower for equity funds, consistent with the results in Table 3. Funds with higher excess kurtosis are more likely to be zero-R^2 funds, perhaps driven by option-like payoffs from positions in exotic securities or dynamic trading, both of which are difficult to capture in style factors. Perhaps surprisingly, more negative expected shortfall decreases the probability of a zero-R^2 fund. This is likely due to the extreme market downturns in the sample. Funds with significant market exposure would then feature both significant R^2 and a thick left tail.

TABLE 6

Determinants of Zero R^2

Listed are results of probit regressions in which the dependent variable equals 1 if a fund's R^2 is insignificantly different from 0, and 0 otherwise. *Age* is the length of a fund's history in months. *Size* is the natural logarithm of the maximum assets under management reached by a fund. *Equity* equals 1 if a fund is in the equity style, and 0 otherwise. *Kurt* is the excess kurtosis of a fund's monthly returns. *ES* is expected shortfall as measured by the average of the lowest 5% of a fund's returns.

	7-Factor		14-Factor	
Determinant	Coeff.	*p*-Value	Coeff.	*p*-Value
Intercept	0.8272	0.0000	0.9884	0.0000
Age	−0.0103	0.0000	−0.0119	0.0000
Size	−0.0063	0.5305	−0.0191	0.0633
Equity	−0.2142	0.0000	−0.3075	0.0000
Kurt	0.0059	0.0176	0.0069	0.0066
ES	3.7441	0.0000	3.3934	0.0000
McFadden R^2	0.1072		0.1211	

In the same spirit of Fung and Hsieh (1997), I contrast hedge funds and mutual funds vis-à-vis the ability of factor models to explain their returns. For the equity mutual fund sample, I use the Carhart (1997) 4-factor model. For hedge funds, as before, I maximize R^2 by selecting for each fund the optimal subset of at most 3 factors.

Figure 1 shows the cross-sectional distribution of R^2 for hedge funds and mutual funds. Graph A shows results using the 7-factor model for hedge funds with constant factor loadings. The vast majority of mutual funds have R^2 above 80%, whereas almost all hedge funds have R^2 below this level. Note that mutual funds have much higher R^2 than hedge funds despite the use of a set of only 4 factors. Graph B shows results when hedge funds are analyzed using the 14-factor model (the hedge fund distribution is shifted somewhat to the right, reflecting the additional factors that mimic a variety of trading strategies). Nonetheless, the difference between mutual funds and hedge funds is still stark. Graphs C and D show results when hedge fund factor loadings are allowed to switch. There

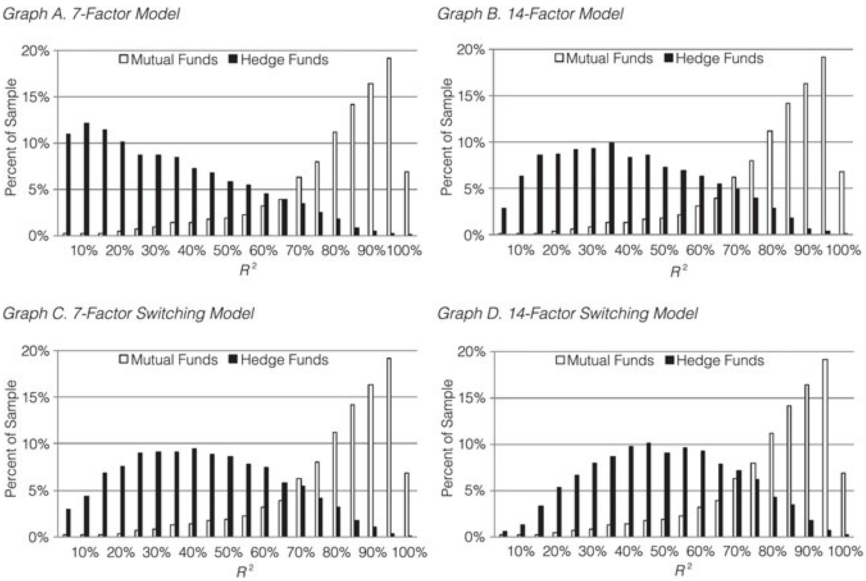
[12]In addition, Liang and Park (2010) use a Cornish-Fisher expansion to establish a parametric threshold. The two thresholds generate highly correlated measures of expected shortfall in the sample; hence, I use the nonparametric approach.

is noticeable improvement, but the pronounced difference between mutual funds and hedge funds remains. These results suggest that factor model regressions may always struggle to yield a great deal of explanatory power for individual hedge funds.

FIGURE 1

Cross-Sectional Distribution of R^2

Depicted are cross-sectional distributions of R^2 in a sample of hedge funds and actively managed equity mutual funds with data through 2008. Hedge fund data are drawn from the CISDM and TASS databases, and mutual fund data are from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. For mutual funds, the factors are the market excess return and the size, value, and momentum factors. For each hedge fund, the optimal subset of up to 3 factors is selected to maximize the R^2. Graphs A and B show results for the 7- and 14-factor models, respectively, in which factor exposures are held constant. Graphs C and D show corresponding results when factor exposures are allowed to switch once during each fund's history.



B. The Presence of Omitted Factors

I form portfolios of zero-R^2 funds to gauge the magnitude of unidentified systematic risk. A benefit of this procedure is that I can detect comovements among the funds without having to specify the source of nondiversifiable risk.[13] If the returns of zero-R^2 funds are truly idiosyncratic, then the volatility of portfolios of these funds should approach 0 as the number of portfolios increases. I randomly form portfolios on January of each year 1996–2007 by selecting without replacement from the subset of funds with zero R^2 using the prior 24 months and reporting returns for 24 months following the portfolio formation date. Each January I construct 10,000 portfolios with size ranging from 1 to 50 funds, then compute the volatility of each portfolio over the next 24 months, assuming a buy-and-hold

[13]An alternative methodology for identifying comovements in returns is principal component analysis, as used in Fung and Hsieh (2001).

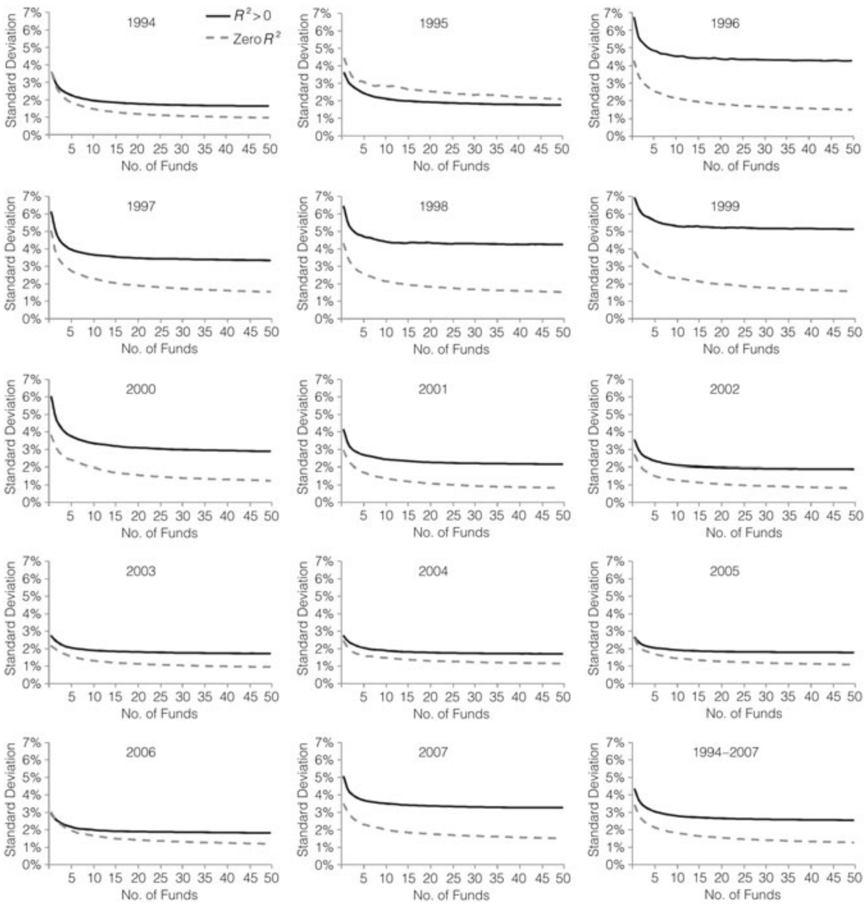
strategy to account for illiquidity due to lockups. I repeat the experiment by selecting instead from the subset of funds with significant R^2. The average volatility of the random portfolios of size 1 is simply the average volatility of individual funds. The average volatility of portfolios with 50 funds gives an indication of the systematic risk of the funds in aggregate. The difference between the volatilities of these two extremes illustrates the idiosyncratic risk of the funds.

Figure 2 shows the results. In all years except 1995, the $R^2 > 0$ portfolios feature higher average volatility than the zero-R^2 portfolios at all portfolio sizes, consistent with the summary statistics for individual funds reported in Table 5. There is substantial time variation in volatility levels for the $R^2 > 0$ portfolios,

FIGURE 2

Systematic Risk

Figure 2 shows the standard deviation of returns, on the vertical axis, for randomly formed portfolios of hedge funds as a function of the number funds in the portfolio, on the horizontal axis. Dashed lines represent portfolios comprised of zero-R^2 funds, whereas solid lines represent portfolios comprised of funds with R^2 significantly greater than 0 as determined by the optimal factor model using each fund's complete history. Buy-and-hold portfolios are formed by drawing without replacement from the set of funds available on January of the year listed in each chart, and they are tracked for 24 months. The graph labeled "1994–2007" shows the average across years.



with higher levels during the dot-com era of 1996–2000 and substantially less during the precrisis years of 2002–2006. Most importantly, in the majority of years there is a limit to the diversification achieved in the zero-R^2 portfolios. At the maximum portfolio size of 50 funds, zero-R^2 portfolio volatility is typically ½ that of the $R^2 > 0$ portfolio volatility, clearly illustrated in the average across the years in the graph labeled 1994–2007. This result indicates that zero-R^2 hedge funds feature about 50% of the systematic risk of the $R^2 > 0$ funds; in other words, widely used factor models have failed to recognize the substantial comovement in returns for a large number of hedge funds in the sample.

I repeat the simulated portfolio analysis on subsets based on whether a fund is in the equity style or not. The levels of systematic and idiosyncratic risk averaged across the years of formation are summarized in Table 7. Panel A indicates that the level of idiosyncratic risk in equity funds that feature zero R^2 is approximately 40% larger than it is in equity funds with $R^2 > 0$. For nonequity funds, the levels of idiosyncratic risk are only slightly larger for the zero-R^2 subset. More importantly, Panel B shows that for both the equity and nonequity subsets, the average level of systematic risk in the portfolios of zero-R^2 funds is fully ½ that of the $R^2 > 0$ portfolios, again indicating that funds for which factor models fail should not be interpreted as generating purely abnormal returns.

TABLE 7

Idiosyncratic and Systematic Risk

Listed are levels of idiosyncratic and systematic risk for subsets of funds based on the significance of R^2 from a 7-factor model. Funds are placed in the 2 categories based on the optimal factor model using the fund's full history. Risk levels are computed annually by selecting funds at random in January and forming portfolios that are held for 2 years. Each year 10,000 portfolios are formed and tracked as buy-and-hold investments. Idiosyncratic risk is the difference between the average volatility of single-fund portfolios and the average volatility of portfolios with 50 funds. Systematic risk is the average monthly volatility of portfolios with 50 funds. "All Funds" shows results using all funds reporting in a given 2-year window. "Equity" and "Nonequity" show results using subsets based on whether the fund is in the long-short equity category or not. "Ratio" is the level of the volatility of zero-R^2 funds as a percentage of the volatility of $R^2 > 0$ funds.

Category	All Funds	Equity	Nonequity
Panel A. Idiosyncratic Risk			
$R^2 > 0$	1.81%	1.78%	1.76%
Zero-R^2	2.12%	2.47%	1.88%
Ratio	116.99%	138.92%	107.30%
Panel B. Systematic Risk			
$R^2 > 0$	2.54%	3.11%	2.11%
Zero-R^2	1.26%	1.60%	1.10%
Ratio	49.61%	51.44%	52.00%

C. R^2 and Hedge Fund Durations

The summary statistics described previously do not reveal any evidence of increased risk in zero-R^2 funds. However, as argued in Section II, the censorship of hedge fund returns that occurs when managers decide to stop reporting may result in downward-biased estimates of risk for failing funds. Fund failures are a less ambiguous indicator of a bad outcome; hence, in this subsection I study the significance of R^2 as a predictor of hedge fund failure.

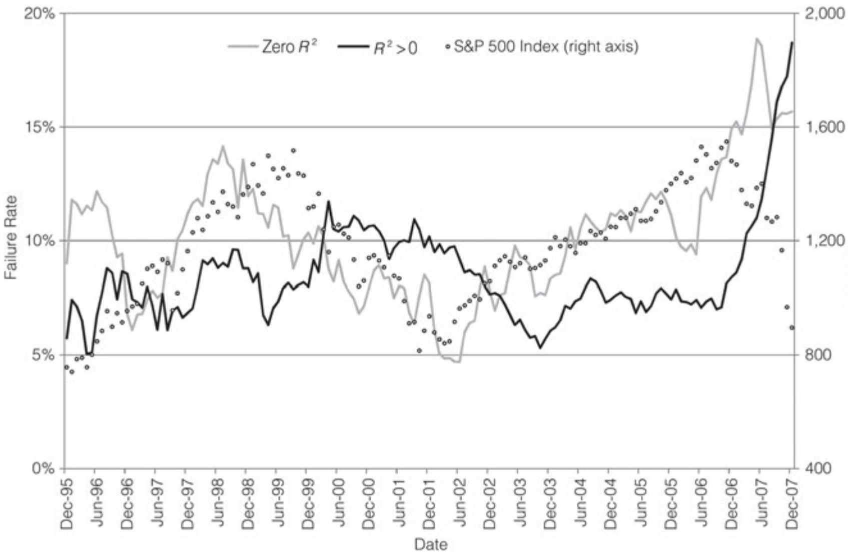
I assume a fund fails when a manager stops reporting following poor performance. The majority of funds cease reporting due to failure, as argued by Ackermann et al. (1999) and Grecu, Malkiel, and Saha (2007); however, some hedge fund managers may stop reporting for good performance. I treat funds that cease reporting with cumulative 12-month returns above the median on the last reporting date as censored observations of live funds.[14] In practice, a failing fund could continue to survive for some period of time after the manager stops reporting. Consequently, my measure likely understates durations.

To provide background, I plot in Figure 3 the level of the S&P 500 index as well as the unconditional probability of failure for zero-R^2 funds and other funds separately. Each month, I determine whether funds in existence for at least 24 months feature a significant R^2 or not, and then track the percentage of each set of funds that fail in the subsequent 12 months. The failure rate of zero-R^2 funds is higher than that of other funds most of the time. The primary exception is the end of the dot-com bubble period. As equity prices fell during 2000–2001, the failure rate of funds with $R^2 > 0$ rose to about 10% per year, while the failure rate of zero-R^2 funds dropped to 5%. One might expect that funds with significant systematic risk would suffer more than other funds during market downturns. Indeed, the

FIGURE 3

Failure Rates

Solid lines indicate the failure rate of hedge funds in the CISDM/TASS database. The dark and light lines indicate the failure rates of 2 subsets of funds: those with R^2 significantly greater than 0 and those with R^2 insignificantly different from 0, respectively. The failure rate on a given month t equals the number of funds that cease reporting within 12 months, with below-median 12-month cumulative returns on the last reporting date, divided by the number of funds reporting on date t. Hollow circles indicate the level of the S&P 500 index.



[14]For robustness, I also applied the definition of failure from Liang and Park (2010): A failed fund is one that stops reporting with negative average 6-month return and assets under management that declined over the prior year. The resulting failure rate is lower, but the relation between the failure rates of zero-R^2 funds and other funds is qualitatively unchanged.

correlation between failure rates and S&P 500 index returns is -0.60 for $R^2 > 0$ funds and –0.02 for zero-R^2 funds. Note, however, that both sets of funds feature a dramatic rise in failures toward the end of the sample, coinciding with the global financial crisis. This result provides preliminary evidence that the zero-R^2 funds are exposed to some unspecified omitted factor. The temporal pattern of failures also indicates the need to use fixed time effects to capture the general rise and fall of failure rates.

I assume that failure rates depend on fund age t and a vector of covariates z. Specifically, the hazard rate λ of an individual hedge fund equals the baseline hazard rate λ_b scaled up or down as follows:

$$\lambda(t,z) \quad = \quad \lambda_b(t)\, e^{z'\beta}. \tag{1}$$

The form of the proportional hazard rate in equation (1) is convenient, because the coefficient vector β can be estimated independently from the baseline hazard rate. The purpose of this exercise is to determine whether a zero R^2 is a predictor of hedge fund failure; hence, one of the covariates is an indicator variable that equals 1 for zero-R^2 funds. Prior research provides guidance regarding the selection of 2 other covariates. Liang and Park (2010) study the power of a variety of downside risk measures to predict fund failure and support the use of expected shortfall. Low cumulative returns affect durations for two reasons. First, managers of funds with low returns are less likely to capture performance fees, since the NAV must recover to previously set high-water marks before the fees accrue. This provides managers of poorly performing funds a strong incentive to close those funds. Second, investors are more likely to withdraw capital from poorly performing funds, forcing the manager to liquidate assets that could lead to a death spiral. I control for style effects by conducting the analysis on equity and nonequity subsets. Last, I include annual fixed effects to capture the changing market conditions illustrated in Figure 3.

I estimate hazard rate coefficients by computing every month, for all funds, *Rank*, their percentile rank compared to all other funds in existence at the same point in time using 12-month cumulative returns; *ES*, their expected shortfall using all observations up to the date in question; and R^2*Flag*, an indicator variable that equals 1 for zero-R^2 funds using the last 24 months of returns up to and including the month in question.[15] The first 2 covariates are demeaned prior to estimation to ease interpretation of the coefficients.

Table 8 gives the results, including coefficient estimates, p-values based on White's (1982) standard errors, and the marginal effect of each covariate. As listed in Panel A, the coefficients on *Rank* and R^2*Flag* are statistically significant for both the 7- and 14-factor models. Also listed is a likelihood ratio test statistic that compares the log-likelihood of the model shown to a model that eliminates R^2*Flag* from the analysis. For both models, the restriction is rejected at the 1% level. Marginal effects show the increase in probability of failure relative to the unconditional probability resulting from an increase in each covariate. The unconditional probability is set to 10%, consistent with Figure 3, in which the hedge

[15]As mentioned in Section II, the rolling window of 24 months accommodates time variation in factor loadings.

TABLE 8

Proportional Hazard Rate

Listed are maximum likelihood estimation (MLE) coefficient estimates, *p*-values based on White's (1982) standard errors, and marginal effects of covariates of a proportional hazard rate of hedge funds. *Rank* is the percentile rank of the 12-month cumulative return compared to all other funds; *ES* is the expected shortfall, defined as the average of returns below the 5th percentile; and R^2 *Flag* is an indicator variable that equals 1 if the corresponding R^2 is statistically significant at the 5% level. Marginal effects show the increase in probability of failure following an increase in each of the covariates when the unconditional annual probability is 10%. For *Rank*, the marginal effect is for an increase from the 50th to the 75th percentile. For *ES*, the marginal effect is for a 1-standard-deviation increase. For R^2 *Flag*, the marginal effect shows the increase in probability when the R^2 is insignificant. Also listed are the χ^2_1 likelihood ratio (LR) test statistic for a difference in the log-likelihood values of the unrestricted model and a restricted model that omits the R^2 *Flag* variable. Results are shown when R^2 *Flag* is determined by a 7-factor model and a 14-factor model.

	7-Factor			14-Factor		
Covariate	Coeff.	*p*-Value	Effect	Coeff.	*p*-Value	Effect
Panel A. All Funds						
Rank	−4.6980	0.0000	−0.0691	−4.7008	0.0000	−0.0691
ES	−0.3585	0.1661	−0.0026	−0.3390	0.2512	−0.0024
R^2 *Flag*	0.1351	0.0011	0.0145	0.1296	0.0016	0.0138
LR test statistic	11.0225	0.0009		10.6427	0.0011	
Panel B. Equity Funds						
Rank	−4.5672	0.0000	−0.0681	−4.5614	0.0000	−0.0680
ES	−0.8787	0.0206	−0.0056	−0.9068	0.0085	−0.0058
R^2 *Flag*	0.0838	0.1911	0.0087	0.1280	0.0410	0.0137
LR test statistic	1.8121	0.1783		4.3086	0.0379	
Panel C. Nonequity Funds						
Rank	−4.7351	0.0000	−0.0694	−4.7409	0.0000	−0.0694
ES	−0.0647	0.8719	−0.0005	−0.0087	0.9838	−0.0001
R^2 *Flag*	0.1745	0.0014	0.0191	0.1305	0.0162	0.0139
LR test statistic	10.3230	0.0013		6.1918	0.0128	

fund industry experienced a 10% death rate for most of the years in the sample. An increase in rank from 50 to 75 decreases the probability of failure by 6.91 percentage points.[16] More importantly, funds with zero R^2 feature an increase in failure rate of 1.45% per year for the 7-factor model and 1.38% for the 14-factor model. Thus, while return rank is by far the most important determinant of fund failure, the coefficient on R^2*Flag* is both statistically and economically significant. This result indicates that, after controlling for other variables, a poor understanding of the return-generating process for hedge funds is a risk factor. Panel B indicates that for equity funds, the coefficient on *ES* is significant but the coefficient on R^2*Flag* is not, using the 7-factor model. For the 14-factor model, however, R^2*Flag* remains significant with an almost identical marginal effect as in Panel A. Panel C indicates that for nonequity funds, the coefficient on R^2*Flag* is statistically significant for both models, again with an almost identical effect using the 14-factor model. In summary, after controlling for performance, expected shortfall, style, and annual fixed effects, the property of zero R^2 is a significant determinant of fund failure.

The proportional hazard rate model implicitly controls for fund age by comparing the characteristics of failed funds to characteristics of all other funds of the

[16]Since other variates are set to their means, and the variates have all been demeaned, the marginal effect is given by $e^{-4.6980\times 0.25} - 1 = -0.691$ for the 7-factor model, which then reduces the assumed unconditional probability from 10% to 3.09%.

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same age. However, I know from the results in Table 2 that the zero-R^2 property is much more pronounced for young funds; hence, a natural question is whether the information content of zero R^2 changes with age. To address this issue, I rerun the proportional hazard rate model on subsets of observations formed by whether a fund was less than 48 months old or not when the observation was recorded. Table 9 presents the results. In all cases, the coefficient on R^2*Flag* is positive and statistically significant at the 10% level. However, the magnitude of the coefficient is roughly 60% larger for younger funds. In the 7-factor model, for example, the coefficient is 0.1689 for young funds versus 0.1080 for older funds. As funds age, the association between a low R^2 and fund failure weakens. A possible explanation for this result is that a low R^2 can be generated by a skillful manager who profits from exploiting arbitrage opportunities and informational advantages, or by a manager who makes idiosyncratic bets or loads up on some unspecified risk. The fund run by the latter manager is more likely to fail, so that a survivor effect will weaken the relation between low R^2 and failure rates for older funds.

TABLE 9

Proportional Hazard Rate by Age

Listed are MLE coefficient estimates, *p*-values based on White's (1982) standard errors, and marginal effects of covariates of a proportional hazard rate of hedge funds. *Rank* is the percentile rank of the 12-month cumulative return compared to all other funds; *ES* is the expected shortfall, defined as the average of returns below the 5th percentile; and R^2*Flag* is an indicator variable that equals 1 if the corresponding R^2 is statistically significant at the 5% level. Marginal effects show the increase in probability of failure following an increase in each of the covariates when the unconditional annual probability is 10%. For *Rank*, the marginal effect is for an increase from the 50th to the 75th percentile. For *ES*, the marginal effect is for a 1-standard-deviation increase. For R^2*Flag*, the marginal effect shows the increase in probability when the R^2 is insignificant. Also listed are the χ^2_1 likelihood ratio (LR) test statistic for a difference in the log-likelihood values of the unrestricted model and a restricted model that omits the R^2*Flag* variable. Results are shown when R^2*Flag* is determined by a 7-factor model and a 14-factor model. Panel A gives results using observations with fund age less than 48 months. Panel B gives results using observations with fund age at least 48 months.

	7-Factor			14-Factor		
Covariate	Coeff.	*p*-Value	Effect	Coeff.	*p*-Value	Effect
Panel A. Young Funds						
Rank	−4.7055	0.0000	−0.0692	−4.7088	0.0000	−0.0692
ES	−0.7046	0.0533	−0.0052	−0.6938	0.0410	−0.0052
R^2*Flag*	0.1689	0.0060	0.0184	0.1614	0.0064	0.0175
LR test statistic	7.9253	0.0049		7.7024	0.0055	
Panel B. Old Funds						
Rank	−4.4834	0.0000	−0.0674	−4.4854	0.0000	−0.0674
ES	−0.1836	0.6109	−0.0013	−0.1517	0.6593	−0.0011
R^2*Flag*	0.1080	0.0543	0.0114	0.0958	0.0812	0.0101
LR test statistic	3.7747	0.0520		3.0669	0.0799	

I add to the proportional hazard rate model the level of residual volatility of each fund's factor model to control for idiosyncratic risk and its impact on the probability of failure, motivated by Pontiff (1996), (2006), who argues that idiosyncratic risk is the most important cost of the pursuit of arbitrage opportunities. Isolating the effect of idiosyncratic volatility also allows one to test for the presence of an omitted factor. Table 10 presents the results. In all cases, the proportional hazard rate model fits the data much more tightly, indicating that *Volatility*,

TABLE 10

Idiosyncratic Risk and R^2

Listed are MLE coefficient estimates, *p*-values based on White's (1982) standard errors, and marginal effects of covariates of a proportional hazard rate of hedge funds. *Rank* is the percentile rank of the 12-month cumulative return compared to all other funds; *ES* is the expected shortfall, defined as the average of returns below the 5th percentile; *Volatility* is the residual volatility computed using the 24 most recent observations; and R^2*Flag* is an indicator variable that equals 1 if the corresponding R^2 is statistically significant at the 5% level. Marginal effects show the increase in probability of failure following an increase in each of the covariates when the unconditional annual probability is 10%. For *Rank*, the marginal effect is for an increase from the 50th to the 75th percentile. For *ES* and *Volatility*, the marginal effect is for a 1-standard-deviation increase. For R^2*Flag*, the marginal effect shows the increase in probability when the R^2 is insignificant. Also listed are the χ^2_1 likelihood ratio (LR) test statistic for a difference in the log-likelihood values of the unrestricted model and a restricted model that omits the R^2*Flag* variable. Results are shown when R^2*Flag* and *Volatility* are determined by a 7-factor model and a 14-factor model.

	7-Factor			14-Factor		
Covariate	Coeff.	*p*-Value	Effect	Coeff.	*p*-Value	Effect
Panel A. All Funds						
Rank	−4.7244	0.0000	−0.0693	−4.7292	0.0000	−0.0693
ES	−1.3301	0.0000	−0.0092	−1.4233	0.0000	−0.0098
Volatility	−4.0657	0.0000	−0.0094	−5.1064	0.0000	−0.0105
R^2*Flag*	0.1766	0.0000	0.0193	0.1774	0.0000	0.0194
LR test statistic	17.3159	0.0000		18.1667	0.0000	
Panel B. Equity Funds						
Rank	−4.5814	0.0000	−0.0682	−4.5789	0.0000	−0.0682
ES	−1.5458	0.0128	−0.0097	−1.7472	0.0002	−0.0109
Volatility	−2.8014	0.2357	−0.0065	−4.0307	0.0235	−0.0082
R^2*Flag*	0.1179	0.1029	0.0125	0.1735	0.0078	0.0189
LR test statistic	3.2331	0.0722		7.1264	0.0076	
Panel C. Nonequity Funds						
Rank	−4.7732	0.0000	−0.0697	−4.7793	0.0000	−0.0697
ES	−1.2951	0.0137	−0.0095	−1.3045	0.0153	−0.0096
Volatility	−5.2070	0.0094	−0.0119	−6.1103	0.0109	−0.0126
R^2*Flag*	0.2215	0.0007	0.0248	0.1808	0.0023	0.0198
LR test statistic	15.3783	0.0001		10.9201	0.0010	

the residual volatility of the regression used each month to determine the significance of R^2, is an important covariate. The coefficient on expected shortfall is now statistically and economically important in all models. In Panel A, the marginal effects of *ES* and *Volatility* are both about 1%. A 1-standard-deviation increase in expected shortfall reduces the failure rate by 0.92% in the 7-factor model, while a 1-standard-deviation increase in residual volatility reduces the failure rate by 0.94%. While the latter result may seem counterintuitive, note that I am controlling for downside risk by including expected shortfall as a covariate, hence higher residual volatility can be interpreted as a measure of managerial activity in the spirit of Titman and Tiu (2011). That said, the coefficient on R^2*Flag* is significant as well, with a larger marginal effect than the coefficients on *ES* and *Volatility*. This result indicates that the impact of an insignificant R^2 on failure rates is not driven by the level of idiosyncratic risk and is likely instead the result of exposure to one or more omitted systematic factors. The economic impact of a zero-R^2 flag is close to 2% per year for the full sample in Panel A, more than double the impact of expected shortfall.

My results may appear to conflict with Fung et al. (2008), who separate funds into those that generate significant abnormal returns and those that do not, labeling the 2 groups "have-alpha" and "beta-only," respectively. Have-alpha funds feature significantly lower liquidation rates than beta-only funds in the years following classification. My results may also appear to conflict with Titman and Tiu (2011), who show that funds with low R^2 tend to outperform other funds in subsequent years. Neither of these papers sorts funds by zero R^2. In unreported results I find that though there is some overlap between the categorizations used in these papers and my categorization based on the significance of R^2, the overlap is far from perfect. Furthermore, my results can be viewed as offering an alternative explanation for the abnormal returns reported in prior hedge fund research. The evidence of systematic risk revealed in the volatility of portfolios of zero-R^2 funds suggests that at least some hedge fund alpha reflects compensation for exposure to one or more omitted factors.

VI. Concluding Remarks

Many hedge funds strive to offer investors a return stream that provides a diversification benefit by featuring low correlation with standard asset classes. I use simulation techniques to identify funds that are market neutral in the sense that an optimal factor model results in a regression R^2 that is indistinguishable from 0. Over ⅓ of the funds in my sample are zero-R^2 funds. The percentage of zero-R^2 funds is decreasing as a function of fund age: Over 50% of funds with histories of less than 36 months are classified as zero-R^2 funds. The zero-R^2 property is found in large numbers of funds across all styles and is robust to procedures that account for backfill, switches in factor exposure, and return smoothing.

I show that portfolios of zero-R^2 funds feature fully ½ the volatility of portfolios of other funds, indicating that factor model regressions can substantially understate the level of systematic risk in hedge funds. Furthermore, in a proportional hazard rate model, I find that the low-R^2 property increases the probability of fund failure, even after controlling for other risk measures, including expected shortfall based on prior returns and the level of residual volatility. This result suggests the presence of an omitted but potentially catastrophic risk factor in funds for which standard regression analysis fails.

My results have important implications for both academic research and the due diligence process for fund selection. When investors are unable to learn about a fund through statistical analysis, there is a heightened risk of failure and the losses that occur as a consequence. An obvious recourse is to learn about the fund and its investment prospects via more qualitative means. The investment decision must therefore rely more heavily on other inputs that are unavailable to the econometrician, such as a manager's background and a more qualitative understanding of a fund's strategy mix.

Academic research on hedge funds often relies on short histories, especially when studying performance persistence. Titman and Tiu (2011), for example, estimate factor models using rolling windows of 24 months when forecasting future performance, and Jagannathan et al. (2010) use 36-month histories. Hypothetical trading strategies and other empirical analyses should be designed to recognize that the information content of factor models weakens considerably when short histories are used.

Appendix A. Hedge Fund Styles

The 2 databases I use in the study, TASS and CISDM, have different style categories. To consolidate, a list of 13 different styles as created. Table A1 shows how the styles of the 2 databases are mapped into the consolidated list of 13 styles. Panels A and B list the styles of the TASS and CISDM databases, respectively, as well as each style's number in the consolidated style list. Panel C gives the style names of the consolidated list.

TABLE A1

Hedge Fund Styles

Listed below are hedge fund styles in the TASS and CISDM database as well as 13 consolidated categories used in the paper.

Category	Style	Category	Style	Category	Style
Panel A. TASS		*Panel B. CISDM*		*Panel C. Consolidated*	
1	Long/short equity hedge	1	Equity long only	1	Equity
2	Multistrategy	1	Equity long/short	2	Multistrategy
3	Event driven	2	Multistrategy	3	Event driven
4	Emerging markets	2	Relative value multistrategy	4	Emerging markets
5	Equity market neutral	3	Event-driven multistrategy	5	Equity market neutral
6	Fixed income arbitrage	3	Merger arbitrage	6	Fixed income
7	Global macro	4	Emerging markets	7	Macro
8	Convertible arbitrage	5	Equity market neutral	8	Convertible arbitrage
10	Options strategy	6	Capital structure arbitrage	9	Sector
10	Other	6	Fixed income	10	Other
10	Undefined	6	Fixed income: mortgage-backed securities	11	Distressed securities
12	Dedicated short bias	6	Fixed income arbitrage	12	Short bias
		7	Global macro	13	Single strategy
		8	Convertible arbitrage		
		9	Sector		
		10	Market timing		
		10	Option arbitrage		
		10	Other relative value		
		10	Regulation D		
		10	Undefined		
		11	Distressed securities		
		12	Short bias		
		13	Single strategy		

Appendix B. Extracting Actively Managed Equity Funds from CRSP

Equity funds are identified by style code. Funds typically have multiple style codes listed in the CRSP style file, and these can change over time. I consider a fund to be an equity fund if the fund has at least one indication of Lipper Asset Code EQ (Equity Funds); Policy Code CS (Common Stock); Strategic Insights Objective Code AGG (Equity USA Aggressive Growth), GMC (Equity USA Midcaps), GRI (Equity USA Growth & Income), GRO (Equity USA Growth), ING (Equity USA Income & Growth), or SCG (Equity USA Small Companies); or Weisenberger Objective Code G (Growth), LTG (Long-Term Growth), MCG (Maximum Capital Gains), or SCG (Small Capitalization Growth). Furthermore, if there is any record of one or more codes that are not in this list (e.g., Policy Code GS (Government Securities)), the fund is not considered an equity fund.

A fund is considered an index fund if at least 1 of 3 conditions are met. The 1st condition is if the CRSP index fund flag equals "B," "D," or "E," corresponding to an index-based fund, a pure index fund, or an index-enhanced fund, respectively. This flag captures roughly ⅓ of the index funds in my sample, since it is only available since 2008. The 2nd condition is if the CRSP exchange-traded fund equals "F" or "N," corresponding

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to an ETF or ETN, respectively. The 3rd condition is if the fund name contains the character string "INDEX," "index," or "Idx."

Appendix C. Estimating True Returns from Smoothed Returns

Decompose true returns into an unconditional mean plus mean-zero noise:

$$R_t = \mu + \varepsilon_t, \quad \varepsilon_t \sim \left(0, \sigma^2\right), \tag{C-1}$$

where $1 \leq t \leq T$. Observed returns are assumed to be a moving average of contemporaneous and lagged returns:

$$R_t^O = \theta R_t + (1-\theta) R_{t-1}, \tag{C-2}$$

which can be written upon substitution of expression (C-1) into equation (C-2) as

$$R_t^O = \mu + \theta\varepsilon_t + (1-\theta)\varepsilon_{t-1}. \tag{C-3}$$

To recover true returns from observed returns, I need to estimate θ. To ease notation, first demean observed returns to eliminate μ. Next, regress observed returns on their 1st lag:

$$R_t^O = \alpha + \beta R_{t-1}^O + \gamma_t. \tag{C-4}$$

After some algebra, the relation between β and θ is given by

$$\beta = \frac{\theta(1-\theta)}{\theta^2 + (1-\theta)^2}, \tag{C-5}$$

and after application of the quadratic formula I can recover an estimate of θ:

$$\theta = \frac{1}{2} + \sqrt{\frac{1}{4} - \frac{\beta}{2\beta+1}}, \tag{C-6}$$

under the assumption that the contemporaneous return gets more weight than the lagged return in equation (C-2).

True returns can now be computed by inferring the residuals ε. Assume that $\varepsilon_0 = 0$, so that, for demeaned returns,

$$R_1^O = \theta\varepsilon_1, \quad \varepsilon_1 = \frac{R_1^O}{\theta}, \tag{C-7}$$

and for $t > 1$, use the recursive formula

$$\varepsilon_t = \frac{R_t^O - (1-\theta)\varepsilon_{t-1}}{\theta}, \tag{C-8}$$

where expressions (C-7) and (C-8) are derived from equation (C-3). True returns can now be estimated by adding the unconditional mean to the estimated series of residuals ε.

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