Evaluating Hedge Fund Performance

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ABSTRACT

A diverse set of measures allows investors to evaluate hedge fund portfolio managers' performance across different dimensions. The various measures quantify the effectiveness of security selection, account for investor flows, operating risk, and worst-case investment scenarios, net out benchmark and peer-fund performance, and control for risk factors that are unique to hedge fund investment strategies. Hedge fund return information in published databases is usually self-reported, which is a conflict of interest that produces several reporting biases and inflated published average returns. After adjusting for these biases hedge fund average returns trail equity market returns and in fact almost exactly equal U.S. Treasury bill average returns between January 1994 and March 2016. Yet, after risk adjustment, the hedge fund performance picture brightens. In the aggregate, hedge funds have higher Sharpe ratios and multi-factor alphas, and lower maximum drawdown levels than equity market benchmarks.

INTRODUCTION

Hedge funds have become increasingly important components of institutional portfolios. The popularity of hedge funds is due to investors' belief that they increase portfolio performance. Potential sources of performance gains could include high average returns, low volatility, positive skewness, and low kurtosis. Related to these characteristics is the hope that hedge fund investments will produce diversification benefits relative to other portfolio holdings.

As this chapter shows, calculating the performance of hedge funds is a nontrivial exercise. A relatively high degree of sophistication is required to choose the data to include and performance calculation method to use. Even then, the task remains to interpret the results in a way that reflects economic reality for investors. Hedge fund performance is usually evaluated relative to each fund's stated objective. In some cases, funds are benchmarked against security market indexes, and in other cases funds' objectives are to achieve a minimum absolute level of return.

Experts disagree about whether hedge funds' performance has justified their widespread veneration and use by institutional investors. Lack (2012) argues that hedge funds in the aggregate have performed poorly during the past several decades. He contends that hedge funds have even failed to keep up with Treasury securities. Lack calls for measuring cross-sectional hedge fund returns not as simple averages, but on an asset-weighted basis, as though the industry itself were one large fund. He also notes that high portfolio management and incentive fees cause hedge fund managers to receive the lion's share of any market-beating return, thus limiting benefits to the ultimate investors.

Taking the opposing position, Zummo (2012) acknowledges that despite individual hedge funds' high incidence of mortality and cross-sectional performance dispersion, they serve a useful diversification function for many portfolios. He also advocates for a strategy followed by the most successful hedge fund investors, who eschew single-portfolio investments and instead deploy their hedge fund allocation in multi-manager, multi-strategy portfolios. This approach can involve a carefully chosen series of individual hedge funds or a well-designed fund of hedge funds.

This chapter is organized as follows. The next section explores the effect of reporting biases and anomalies on performance calculation, followed by a section that discusses hedge fund performance measures and applies them to data. Then, the chapter considers the relation between performance and hedge fund characteristics. The chapter concludes with a summary.

SELECTING DATA TO USE IN PERFORMANCE EVALUATION

Several issues arise when selecting the appropriate data to use in evaluating hedge fund performance. Published hedge fund data are replete with biases, most of which make investment results seem better than they are. Using such results makes portfolio managers appear to possess a level of skill that they do not. Moreover, because hedge funds self-report their returns to databases, investors and researchers must be aware of the severe conflicts of interest that this situation creates. This section provides a discussion of the principal biases and reporting anomalies.

Biases

This chapter contains updated performance results for hedge funds between January 1994 and March 2016. Results are initially shown in raw form just as they appear in the database, before adjusting for known biases. Then, in sequence, new results are generated after controlling for biases. Liang (2000) notes various errors and inconsistencies across hedge fund databases and concludes that TASS is the best database to use for academic research. The former Lipper/TASS is now known as the Thomson Reuters Lipper Hedge Fund Database, which is the database used in this chapter.

Table 23.1 contains monthly average hedge fund returns for January 1994 through March 2016. This table includes all months of data for all funds in the Thomson Reuters Lipper Hedge Fund Database. Managed futures, long-short equity, and event driven are the highest-returning strategies, on average, while funds of funds, dedicated short bias, and emerging markets are the lowest-returning strategies during the study period. As a comparison, the bottom of Table 23.1 shows that average return for both the Standard & Poor's (S&P) 500 Index and Russell 2000 Index are higher than the average hedge fund return by about 30 basis points.

(Insert Table 23.1 about here)

Hedge fund performance data suffer from several well-known biases including one that arises from the tendency of hedge fund managers to start and “incubate” multiple funds simultaneously. All the funds then operate until they have amassed a performance record long enough to report to databases. A self-selection bias occurs because among the multiple funds, fund managers add any outperformers to databases, while they quietly close and never add underperforming funds. Investors who committed money to all of the hedge funds at the start of the incubation period would have earned a lower return than the surviving funds reported to the databases.

A related bias arises when the fund manager retroactively submits the initial months of a surviving hedge fund’s reported returns to databases (i.e., “backfilled”). Given the positive record, due to mean reversion and the aforementioned self-selection bias, the fund’s subsequent returns are likely to be lower than returns from the start-up period. Thus, overall reported return is almost certainly an excessively positive reflection of the average investor’s experience.

Table 23.2 brings this concept of “backfill bias” into stark relief. The first column of returns is repeated from Table 23.1. These returns reflect all months of reported performance. The second column contains average returns for only the first 18 months of each fund’s reported returns, while the final column consists of returns subsequent to month 18. Without exception, the average returns for months 1 through 18 exceed the average returns for subsequent months. The arithmetic average monthly return for all funds in the latter period is 0.23 percent, less than half the 0.50 percent reported for the entire sample period. For the fund-of-funds (FOFs) strategy, the average return is negative. For 11 of the 13 hedge fund strategies, the average returns in the two periods differ by more than a factor of two. Because of this bias, researchers often omit reported returns from the initial months of a hedge fund’s life.

(Insert Table 23.2 about here)

Table 23.3 captures another bias in reported hedge fund returns. Hedge funds regularly experience mortality, but in some years the rate of attrition is very high. As Fung and Hsieh (1997b) observe, about 20 percent of their sample of commodity trading advisors (CTAs) shut down each year. Liang (2001) finds an attrition rate of only 8.5 percent, but the cumulative effect is striking. Of the hedge funds contained in the Thomson Reuters Lipper Hedge Fund Database, less than one-third still operate today. When using historical data, an analysis using only surviving funds produces an excessively positive performance picture. This bias is called *survivorship bias*. Table 23.3 shows that average monthly returns for funds that remain in operation (a "Live" subsample) are 0.43 percent, and monthly returns for funds that no longer operate (a "Graveyard" subsample) are 0.15 percent. For every hedge fund strategy, Graveyard subsample returns are lower than Live subsample returns. To avoid survivorship bias, any proper analysis must incorporate all funds from both subsamples.

(Insert Table 23.3 about here)

Hedge fund reported returns may not accurately reflect returns available to all investors because some funds are closed to new investors. Almost 800 funds currently listed in the Thomson Reuters Lipper Hedge Fund Database have been closed at some point, and more than 700 of these have never reopened. Other fund characteristics such as high minimum initial investments also serve to limit the applicability of calculated performance figures to investors in general. Henceforth in this chapter, to minimize backfill bias and survivorship bias, all original performance figures are measured after month 18 and results contain both the Live and Graveyard subsamples.

Table 23.4 shows the distributional properties of hedge fund monthly returns. Consider first the left half of the table. The bias-free average return on hedge funds is 0.23 percent, equal to the average return on the 3-month U.S. Treasury bill (T-bill) shown one line below it. With respect to the standard deviation of returns, the lowest values are for convertible arbitrage, fixed income arbitrage, and event driven funds. The highest values are clearly for multi-strategy, followed by equity market neutral and long/short equity hedge. The overall monthly standard deviation of 3.30 percent corresponds to an annualized figure of 11.43 percent. Skewness values are almost uniformly negative, with the exceptions being short bias, global macro, and managed futures. Nine of 13 kurtosis figures are above 3.0, suggesting that most of the hedge fund return distributions are more peaked and have fatter tails (i.e., leptokurtic) than normally distributed returns. From an investor's perspective, the effects of kurtosis are conditional on whether skewness is positive or negative. For example, as Ineichen (2007) notes, a combination of negative skewness and fat tails is especially problematic for investors seeking to avoid negative outcomes.

(Insert Table 23.4 about here)

Consider also the magnitude of minimum and maximum monthly returns in Table 23.4. Many of them are exceptionally high. Although these extreme values are infrequent, they are so large that they risk influencing the analysis excessively. As a consequence, many researchers elect to use a process known as "winsorizing," in which all extreme-tail values are reported at a specified less-extreme level. For example, a common approach is to winsorize at the 1 percent and 99 percent level, meaning that all extreme negative (positive) values are reset at the 1^{st} (99^{th}) percentile value. Then, analyses are conducted assuming that the winsorized distribution properly characterizes the native distribution. The right-hand side of Table 23.4 shows the distributional properties of this chapter's hedge fund return sample after being winsorized at the 1 percent and 99 percent levels. The lower standard deviation and kurtosis numbers are as expected because the winsorizing process creates thinner tails. Given that no formal statistical tests are being run in this chapter, Tables 23.5, 23.6, and 23.7 present return numbers in unwinsorized form.

Table 23.5 presents other common performance measures. The percent of months in which the average hedge fund's returns are positive is 61 percent. Across fund strategies, the figures vary from 51 percent for dedicated short bias funds to 74 percent for fixed-income arbitrage funds. Another key hedge fund measure is *maximum drawdown*, which is the total loss an investor would have experienced from buying at the maximum value reached by a hedge fund and selling at the subsequent lowest point. Based on this measurement criterion, hedge funds outpace the stock indexes, each of which suffers a maximum drawdown worse than –50 percent between mid-2007 and early 2009. The dedicated short bias and emerging markets hedge fund strategies clearly produce the highest average maximum drawdowns of about –40 percent, while six other strategies have returns at less than half those levels.

The Sharpe and Sortino ratios are particularly high for multi-strategy and fixed-income arbitrage. The *Sharpe ratio* is the average return on the managed portfolio net of the risk-free rate divided by the standard deviation of the portfolio return. The *Sortino ratio* is calculated identically except the denominator is a *semi-deviation*, which is a standard deviation that includes only returns below the mean return. Although by using a semi-deviation the Sortino ratio adjusts for asymmetric return distributions, the strategy rankings based on the Sharpe and Sortino ratios are almost identical, meaning that calculating the Sortino ratio may have been unnecessary in this case.

(Insert Table 23.5 about here)

Return Reporting Issues

Hedge fund performance can be evaluated effectively only to the extent the input data are accurate and timely. Because systematic biases described previously are well-known, researchers and investors have adapted their practices and expectations accordingly. A more pernicious irregularity occurs when a hedge fund misreports or delays reporting returns. Aragon and Nanda (2014) examine the performance reporting process for hedge funds. They find that funds with poor returns tend to report late, by an average of almost two weeks. Funds with more illiquid holdings tend to report even later. Managers often cluster their announcements of a period's poor returns with information about positive returns in a partial subsequent period, apparently to mitigate the negative investor response to the full-period disclosure. Although investors commit less capital when performance is poor, timely disclosure could make the situation even worse for the funds. Aragon and Nanda also find that late-announcing hedge funds exhibit subsequent returns that are 3 percent lower than their peer funds.

Bollen and Pool (2009) observe that the distribution of reported monthly hedge fund returns contains a marked discontinuity around 0 percent. They conclude that hedge fund managers strive to avoid reporting return levels that are even slightly negative. Reported small positive returns are much more frequent than reported small negative returns. Bollen and Pool use data from the CISDM database between 1994 and 2005. Figure 23.1 replicates Bollen and Pool's Figure 2b, using this chapter's new data from Thomson Reuters' Lipper Hedge Fund Database between 1994 and March 2016. The updated results are not as striking as those of the original paper, but an anomaly is still detectable in Figure 23.1. In the range of negative returns the relative frequencies increase smoothly until reaching 0 percent. Suddenly, a discontinuity appears, and the proportion of returns slightly above 0 percent is markedly higher. In Figure 23.1, incrementing by one bin between Bins –3 to +3, the change in frequency in each case is between 0.35 percent and 0.55 percent, with the exception of Bin 0 (the first positive bin), which has an increase in frequency of 1.02 percent.

(Insert Figure 23.1 about here)

Liang (2003) reports that hedge fund return discrepancies across different databases relate to whether the hedge fund subjects itself to a formal accounting audit. Liang finds that only about 60 percent of hedge funds undergo audits annually and that the lack of an audit also increases a fund's likelihood of ceasing operations.

Cici, Kempf, and Puetz (2015) document that 7 percent of the equity positions of hedge funds are reported at values that deviate from those in the CRSP database. The proportion of negative deviations is higher than the proportion of positive deviations. However, the distribution is non-random. Funds with poor past performance are especially likely to mark position values up, and managers who self-report to public databases are the most prone to record prices at marked-up levels. Indeed, after managers join a database they become more likely to produce positive deviations. Overvaluation has implications for investors, as previous investors can redeem shares at reported net asset values (NAVs) that exceed intrinsic value, while new investors must pay more than the true NAV.

Operational Risk Measure

In recognition of the vulnerability of hedge fund reported returns to shortcomings in its operations, Brown, Goetzmann, Liang, and Schwarz (2009) develop a summary measure of hedge fund operational risk. Their measure, which they call an *omega (ω) score*, takes account of factors such as fund size and age, and potential conflict-of-interest indicators such as whether other firms (e.g., broker-dealer) in a hedge fund's business are related parties, and whether fund employees are allowed to transact in securities in which the fund has a position. Brown et al. find that their ω-score significantly predicts hedge fund returns. They also report that their operational score is related to subsequent financial risk, suggesting that poor operational controls have a direct impact on financial performance and also an indirect effect through financial risk.

HEDGE FUND PERFORMANCE MEASURES

Ackermann, McEnally, and Ravenscraft (1999) conduct one of the first published evaluations of hedge fund return performance. Their sample of 906 hedge funds outperforms mutual funds, but not market indexes. They find that hedge funds are riskier than mutual funds, but offer higher Sharpe ratios over certain time periods. In their sample, hedge fund returns are generally higher gross but not net of fees.

Importantly, Ackerman et al. (1999) conclude that despite the ambiguous results concerning the asset class's return performance, hedge funds contribute significantly to overall portfolio performance through its diversification benefits. Following Elton, Gruber, and Rentzler (1987), they evaluate hedge funds' contribution to a pre-existing portfolio by imposing the requirement that the Sharpe ratio for hedge funds must exceed the product of the pre-existing portfolio's Sharpe ratio and its return correlation with hedge funds. Ackerman et al. conclude that hedge funds satisfy this criterion in all periods, with Sharpe ratios ranging between 0.14 and 0.30.

Liang (2001) reports on hedge fund returns for the decade of the 1990s. Hedge funds as a group underperformed the S&P 500 Index, but they experienced far lower risk which produced relatively strong risk-adjusted performance. One of Liang's most notable observations is that in 1998 the entire hedge fund industry experienced a dramatic decrease in returns and attendant increase in risk and hedge fund mortality. This outcome had the effect of bursting many investors' preconceptions of hedge funds as reliable, all-weather producers of positive excess returns. A decade later, in 2008, hedge funds repeated this story in a greatly magnified fashion.

Sharpe Ratio Criticisms

Ackerman et al. (1999) and others use the Sharpe ratio as a prime measure of hedge fund portfolio performance. Yet, some criticize the Sharpe ratio for several reasons. As Yau, Schneeweis, Robinson, and Weiss (2007) note, several return characteristics and reporting conventions of hedge funds make the Sharpe ratio an upwardly biased measure. First, many hedge funds hold illiquid securities whose prices are subject to estimation procedures resulting in smoothed returns and hence downwardly biased standard deviations. Illiquid holdings can also cause positive autocorrelation among portfolio returns, which produces depressed standard deviations. Second, given that hedge fund returns are skewed and have excess kurtosis, the standard deviation fails to fully capture risk, leading to inflated Sharpe ratios. In view of the asymmetric return distributions for many hedge funds, a more suitable measure is the Sortino ratio.

Persistence and Strategy-adjusted Performance

Brown, Goetzmann, and Ibbotson (1999) examine “offshore” hedge funds domiciled outside the United States. Offshore funds have traditionally been set up to avoid restrictions imposed by the Investment Company Act of 1940, which limits the number of investors in a given hedge fund. With this different sample, Brown et al. confirm the essential results of Ackerman et al. (1999) including that hedge fund managers generate positive risk-adjusted returns. However, Brown et al. concede that given the high attrition rate for funds, their use of annual data imparts a possibly severe positive survivorship bias to the results. Consistent with earlier findings of Fung and Hsieh (1997a), Brown et al. report that hedge fund managers often follow such dynamic strategies that classification of portfolios using Sharpe’s (1992) style-based model tends to be futile. They also find little evidence of performance persistence among funds or managers.

Agarwal and Naik (2000) reiterate Brown et al.’s (1999) basic result for periods longer than one quarter, but they observe significant persistence for all hedge fund types in shorter periods, particularly quarterly. Agarwal and Naik measure outperformance based on whether a hedge fund’s return in a given period is above the average return for all hedge funds following that same strategy. Their second measure is the *appraisal ratio*, which is the alpha from the market model divided by the regression’s residual standard deviation. In this case, the explanatory variable in the market model is not a stock index return but instead is the average return on all hedge funds using the same strategy.

Jagannathan, Malakhov, and Novikov (2010) use a similar approach to measure hedge fund performance. They calculate return for each fund net of the average return for funds pursuing its investment strategy. For example, a fund that uses an event-driven strategy would have its return netted against the average return for funds pursuing that investment strategy. The use of their peer-group approach controls for various complications including nonlinear payoffs, as well as positive autocorrelation resulting from illiquid portfolio holdings.

Risk-factor Models

Researchers have made extensive use of risk-factor-based performance evaluation models in evaluating portfolios, most notably including mutual funds. Since hedge funds have come into the investment mainstream, risk-factor models have been developed to address this specific type of portfolio. The risk-factor-based performance models have different components yet they share a basic form, as Equation 23.1 shows.

$$RP_j = \alpha_j + \sum_k \beta_{jk} RP_k, \tag{23.1}$$

where RP_j and RP_k are risk premia on fund j and risk factor k.

The market model of Jensen (1968) has a single risk factor, the market risk premium calculated as the return on the market portfolio net of the risk-free rate. The three-factor model of Fama and French (1992) includes the market risk premium, a firm size premium (return on small-cap stocks less the return on large-cap stocks), and a style premium (return on value stocks less the return on growth stocks). For the Carhart (1997) model in Equation 23.1, the value for k is four. This model contains the three Fama-French factors plus a momentum factor (return on high-momentum stocks less the return on low-momentum stocks).

In all cases, the estimated intercept (α_j) of the models is used as the measure of each hedge fund manager's skill at generating performance in excess of market performance from a buy-and-hold strategy. The *t*-statistic associated with each estimated intercept is loosely related to the concept of an information ratio, as developed by Treynor and Black (1973). The *information ratio* is a ratio of average portfolio returns net of the returns on a benchmark to the standard deviation of those net returns. For both measures, the performance level is divided by a number that indicates the estimate's precision.

Researchers frequently use the foregoing models to evaluate the performance of institutional portfolios such as mutual funds. Hedge funds can exploit a wider diversity of investment opportunities and their categories span many global markets, asset classes, investment objectives, and constraints. Accordingly, evaluating hedge funds requires a wider array of risk factors. Fung and Hsieh's (2004) seven-factor model is accepted as the standard for performance evaluation in the hedge fund realm. This section presents the seven factors. The first two represent buy-and-hold strategies in the equity market, the next two represent buy-and-hold strategies in the bond market, and the final three are trend-following factors.

- Factor 1. The U.S. equity market risk factor is measured using the S&P 500 Index monthly return.
- Factor 2. A U.S. equity market capitalization risk factor is measured using the Russell 2000 small-cap index monthly return less the S&P 500 Index monthly return.
- Factor 3. A bond market risk factor is measured as the month-to-month change in yield on the 10-year U.S. Treasury bond.
- Factor 4. The credit spread in the U.S. market is measured as the average yield on Moody's Baa-rated corporate bonds less the 10-year U.S. Treasury yield. The credit-spread factor in Fung and Hsieh's model is defined as the month-to-month change in credit spread.

The 5^{th}, 6^{th}, and 7^{th} factors are based on Fung and Hsieh's (1997a, 2001) observation that the typical portfolio positions of hedge funds produce investment payoffs that are distinct from the payoffs seen in more-traditional portfolios. Many hedge funds tend to follow dynamic trading strategies rather than a buy-and-hold approach, so standard factor models are insufficient for modeling returns. Moreover, many hedge funds identify trends in various markets and trade based on those trends. Trends can be positive or negative, and with their investment flexibility hedge funds can exploit such trends by taking long or short positions.

Fung and Hsieh (1997b) conduct a principal-components analysis of CTAs and determine that the principal factor driving returns of that hedge fund strategy relates to trend-following. Fung and Hsieh (1997a) also observe that funds claiming to invest based on trend following experience the highest returns during top- and bottom-quintile financial market performance. Thus, the linear correlation between hedge fund returns and financial market returns is low. Building on the work of Merton (1981), Fung and Hsieh conclude option positions best capture hedge funds' unusual payoffs from following trend-following strategies. Specifically, payoffs to simple long and short trend-following strategies are well represented by a *straddle position*, which is a simultaneously held call and put.

Fung and Hsieh (1997a) identify a lookback straddle as offering the best characterization of trend-following hedge fund payoffs. A *lookback straddle* consists of a lookback call and lookback put. For the former, on the option expiration date the holder identifies the maximum price the underlying reached during the option's life. If that maximum price exceeds the strike price, the investor receives the difference between that maximum and the strike price. The payoff on the lookback put is evaluated similarly, except using the minimum price for the underlying during the option's life. Fung and Hsieh estimate the return to lookback straddles for three distinct markets: the bond market, currency market, and commodity market. The returns to these respective lookback straddles constitute Factors 5, 6, and 7. Fung and Hsieh provide these factors monthly at the website (http://faculty.fuqua.duke.edu/~dah7/HFData.htm).

Finally, researchers use an augmented version of the Fung and Hsieh model for emerging market hedge funds. An 8^{th} factor captures the return on emerging equity markets. This factor is measured using the monthly return on the MSCI Emerging Market Index.

Table 23.6 shows the estimated monthly alphas for hedge funds between January 1994 and March 2016. The numbers underscore the importance of using a set of risk factors that is germane to the types of investments and payoffs that characterize hedge funds. The estimated degree of managerial skill evidenced across fund strategies and in the aggregate varies dramatically among one-, three-, four-, and seven-factor risk models. On average, hedge fund managers generate positive returns net of risk factors over this period that exceeds two decades. Emerging market hedge funds only are evaluated using the eight-factor model.

(Insert Table 23.6 about here)

Money-weighted versus Time-weighted Returns

Following the basic process advocated by Friesen and Sapp (2007) for mutual funds and implemented by Dichev (2007) for stocks, Dichev and Yu (2011) examine the actual returns earned by hedge fund investors. Due to investment and redemption decisions, calculated portfolio returns likely misstate the returns received by the average hedge fund investor. Portfolio returns are usually reported as compound average returns, also known as *time-weighted returns*. Yet, calculating returns earned by the average investor in a portfolio involves weighting each period's returns by the assets under management (AUM) at the start of the period. The so-called *money-weighted return* is determined as the internal rate of return that relates funds invested versus funds redeemed.

Dichev and Yu (2011) find that between 1980 and 2008, the average hedge fund investor made investment and redemption decisions that worked to their disadvantage – investing new capital just before a poor-return period and redeeming funds just before a high-return period. The authors report lower money-weighted return than time-weighed return regardless of the percentile of the hedge fund's reported return. Money-weighted returns also lag time-weighted returns regardless of subperiod, and whether the portfolio is a hedge fund, fund of funds (FOFs), or CTA. Over their entire sample period, money-weighted hedge fund returns trail the S&P 500 index by 4.9 percent annually, and outperform 1-month U.S. Treasury-bills (T-bills) by only 40 basis points annually. An obvious inference from these results is that despite their status as high-net-worth investors, hedge fund investors fall prey to the temptation to engage in return-chasing behavior, just as stock and mutual fund investors do.

Manipulation-proof Performance Measures

Ingersoll, Spiegel, Goetzmann, and Welch (2007) show that many common performance measures are subject to manipulation and gaming by portfolio managers. The gameable measures include the Sharpe, Sortino, Treynor, and information ratios as well as Jensen's alpha. The authors express that manipulation is not in the interest of the ultimate investor because apparent outperformance claimed using a gameable measure may lead to higher fees and career longevity for managers who actually lack skill or an information advantage. Over time, the granting of excessive rewards to such managers will cause more managers to manipulate results. Ingersoll et al. note that hedge fund managers can take simple steps such as writing options and investing the proceeds in U.S. T-bills to change the nature of the underlying return distribution and achieve impressive performance ratios.

Ingersoll et al. (2007) propose what they term a manipulation-proof performance measure (MPPM) that accounts for the hedge fund portfolio's monthly risk premium. Including an estimated risk-aversion coefficient in their measure, the output can be considered a certainty-equivalent level of return. For example, given the specified risk-aversion coefficient, a value for the Ingersoll et al. MPPM of 11 percent is interpreted as meaning that the portfolio's return is equivalent to earning a risk-free return of 11 percent over the time period examined. Although this particular MPPM has not achieved widespread implementation among investors, Ingersoll et al. point out that their measure is very close to the "Risk-Adjusted Rating" developed in 2002 by Morningstar for mutual funds.

Bayesian Approach using Bootstrapping

Kosowski, Naik, and Teo (2007) challenge the notion that hedge fund portfolio managers do not outperform. They employ a Bayesian approach that previously had been applied only to mutual funds to overcome a series of known biases in hedge fund return series. Although their statistical significance is not very strong, they confirm that hedge fund performance reveals skill rather than luck for a subset of managers. With regard to the notion that skill is predictable for periods of a year or more in contrast to earlier findings showing persistence for quarterly horizons only, Kosowski et al. report that their nonparametric results are far more precise and discriminating than parametric alpha estimates.

HEDGE FUND PERFORMANCE AND FUND CHARACTERISTICS

Substantial evidence exists that hedge funds suffer diminishing returns to scale. To the extent that a hedge fund's manager seeks outperformance by pursuing strategies with limited investment capacity, the fund's outperformance is likely to continue only as long as the strategy can continue to be implemented. Other hedge fund characteristics are also associated with performance, as discussed in this section.

Relation between Fund Return and Assets under Management

A question of concern for any investment vehicle is the extent to which portfolio managers' best investment ideas are scalable. For example, if managers detect opportunities in an illiquid security or market segment, their transactions to pursue the opportunity can cause market prices to move enough to wipe out the profit potential. An inability of hedge funds to increase AUM without harming investment performance would reflect diseconomies of scale. Conversely, substantial fixed operating costs exist in managing a portfolio, and spreading those costs over the largest possible asset base will minimize the expense ratio per dollar invested.

Berk and Green (2004) present a model that relates a commingled portfolio's performance with investor flows and hence fund size. As a small portfolio outperforms, high quality rankings awarded by independent entities such as Morningstar cause investor capital flows to the fund increase. As fund size grows, fund performance decreases due to diseconomies of scale. Investors eventually redeem, but this occurs only with a lag. One of Berk and Green's prime contributions is to show how large yet underperforming funds can persist. Although their analysis centers on mutual funds, it also may apply to the hedge fund industry.

Empirical evidence is mixed on the relation between hedge fund size and performance. Fung, Hsieh, Naik, and Ramadorai (2008) find support for Berk and Green's predictions.

Outperforming hedge funds attract significantly higher investor flows than underperforming funds, and subsequent performance of the top funds diminishes as their scale increases.

Teo (2009) finds a strong negative relation for hedge funds between 1994 and 2008. The average annual excess return difference for the smallest 40 percent of funds versus the largest 40 percent of funds is 3.65 percent. In contrast to prior studies that commonly use the Sharpe ratio to measure risk-adjusted returns, Teo calculates excess returns based on the seven Fung and Hsieh (2004) risk factors. He also measures fund size at the start of each period, which controls for the look-ahead bias that sometimes afflicted prior studies. Finally, Teo uses both the Lipper/TASS and HFR databases. His results document the superiority of small funds for all distinct hedge fund strategies, in all regions, and across various fee and management-team structures. The lone exception is the FOFs strategy, for which excess returns are invariant to fund size. This evidence suggests that the FOFs strategy is far more scalable than the distinct hedge fund strategies.

In a study that examines hedge funds between 2005 and 2014, Clare, Nitzsche, and Motson (2015) use the Thomson Reuters Lipper Hedge Fund Database. For their entire sample period, they find a negative relation between performance and fund size. The difference in raw return between the smallest quintile and the largest quintile is 18 basis points a month. The authors then measure excess return as each fund's monthly return net of the return for the HFR index that follows that fund's strategy. The difference in excess return between the smallest and largest size quintiles is 20.5 basis points a month. Interestingly, Clare et al. find that the most dramatic advantage of small vs. large funds occurs during subperiods associated with financial market crises: 1999 to 2000 (technology bubble) and 2008 to 2010 (global financial crisis). This finding adds to past evidence by Brunnermeier and Nagel (2004) about hedge funds' behavior during the technology bubble period. Contrary to expectations, Clare et al. (2015) find that equity hedge funds' ability to take short positions did not diminish the bubble but instead contributed to it. Their analysis of hedge fund holdings reveals that hedge funds bought overpriced technology stocks as the bubble formed, and then sold at a profit shortly before it popped. Their analysis did not distinguish among funds of different sizes.

Table 23.7 shows more recent data from the Thomson Reuters Lipper Hedge Fund Database. In general, the period between April 2011 and March 2016 was kind to large hedge funds. Panel A reveals that the monthly raw returns for top-size-quintile funds exceeded those of bottom-quintile funds by 33 basis points a month. Consistent with Teo's (2009) findings, the FOFs strategy leads the way, with a huge advantage accruing to large-scale funds. By contrast, smaller emerging market and multi-strategy funds tend to dominate. Panel B is largely consonant, with small funds outperforming by an average margin of 60 basis points. After controlling for Fung and Hsieh's seven risk factors plus an eighth for emerging markets funds, the relative advantages of small and large funds flip for emerging markets, long/short equity hedge, and multi-strategy.

(Insert Figure 23.2 about here)

Figure 23.2 shows the results more granularly. The highest average excess returns are generated by the second-largest-decile funds, and the lowest – actually negative – by the smallest. The relation is non-monotonic, but generally favors larger funds. All size quantiles described here and shown in Table 23.7 and Figure 23.2 are constructed as of the start of the performance measurement period, so no look-ahead bias is present. In summary, during the period between April 2011 and March 2016, the negative size-performance relation documented in early studies (Ding, Shawky, and Tian 2009; Teo 2009) reversed for hedge funds overall. Thus, recent investors have not witnessed diseconomies of scale across this industry.

Cross-sectionally, hedge fund sizes are not uniform. Panel C of Table 23.7 shows that at year-end 2015, half of all hedge funds have less than $34 million in AUM, and one-quarter have less than $10.3 million. Fewer than 10 percent of funds are above half a billion dollars in size.

(Insert Table 23.7 about here)

Other Characteristics Related to Performance

Sun, Wang, and Zheng (2012) identify strategy distinctiveness as a key performance attribute of hedge funds. Their hypothesis is that to achieve consistent outperformance, hedge fund managers must successfully innovate. This involves deviating from the investment tactics followed by most peer funds and avoiding crowded trades. The authors investigate the correlation of each hedge fund's historical returns to returns on average funds pursuing the hedge fund's strategy. They calculate their "strategy distinctiveness index" (SDI) as one minus the correlation coefficient. Sun et al. find that subsequent returns are positively related to the SDI level and that level is persistent over time. Thus, high-quality hedge fund managers tend to avoid herding behavior, and their performance is higher than peers, even on a risk- and style-adjusted basis.

Other authors find that the application of certain systematic investment approaches is a key determinant of hedge fund performance. For example, Chen (2011) shows that hedge funds using derivatives can control risks of all types much more effectively than non-users. However, he finds that investors do not tend to reward lower-risk managers by making higher commitments of capital. According to Smith, Wang, Wang, and Zychowicz (2015), hedge funds using technical analysis as opposed to fundamental analysis as their prime investment technique outperform under certain circumstances. Specifically, in *high-sentiment periods* (i.e., when speculative behavior characterizes the market environment) users of technical analysis outperform non-users, after controlling for hedge fund characteristics including the Fung and Hsieh risk factors. In low-sentiment periods, the relation is reversed and fundamental analysis users tend to outperform.

Unlike passively managed institutional portfolios such as indexed mutual funds, hedge funds are almost all managed actively, with an objective of outperforming an index or producing a stable return. Given the high fees charged by hedge fund managers, investors are sensible to question the degree to which such portfolios are actively managed. Miller (2007) develops a simple method for assessing the degree to which actively managed mutual funds deviate from their performance benchmarks in pursuit of alpha. For U.S. large-cap equity funds, Miller reports an active share of only 15 to 20 percent. Thus, such funds hew closely to benchmark indexes while charging fees to investors in excess of 100 basis points. *Active share* is a measure of the degree to which security holdings in a manager's portfolio differ from security components of the benchmark index. Miller shows that given his active share findings and assuming a cost of indexing of 18 basis points, the implied expense ratios for just the active management is approximately 7 percent.

Following Miller's (2007) earlier analysis of mutual funds, Smith (2014) examines equity hedge funds between 1996 and 2013. He documents that equity hedge funds have average active share of about 53 percent. Smith reports the average annual expense ratio for hedge funds' active share is about 7 percent, a figure that is close to Miller's (2007) number for mutual funds. This result suggests that the pricing of active portfolio management services is remarkably uniform.

Smith (2014) also tests the notion that the degree of cross-sectional return dispersion is a proxy for the market's available alpha. Under this hypothesis, the most successful equity hedge fund managers should generate alpha that is positively related to market return dispersion. The study's results strongly confirm the hypothesis, and the relation is robust to various models of the return-generating process. A practical implication is that equity hedge fund managers could potentially use the market's current level of dispersion to tactically adjust the degree to which the investment approach is active or passive. Similarly, hedge fund investors with timely liquidation rights could profitably time their investments and redemptions according to the market's level of cross-sectional return dispersion.

SUMMARY AND CONCLUSIONS

Various performance calculations for a hedge fund can lead investors to different conclusions about whether the manager has outperformed or underperformed. Well-known biases in hedge fund data include incubation bias, self-selection bias, backfill bias, and survivorship bias. Unless such biases are corrected, each can result in hedge fund reported returns exceeding the actual return experienced by investors. Hedge funds also report returns to databases voluntarily and often without independent oversight, so portfolio managers have incentives to misvalue illiquid holdings and otherwise smooth returns. Performance measurement is further complicated by the fact that hedge funds often carry leverage and payoff patterns for certain strategies tend to be nonlinear and return distributions frequently have fat tails and high skewness.

Performance is calculated in many ways. Simple methods include raw return, return net of the risk-free rate, return net of the average for funds following the strategy, percent of months with positive returns, and maximum drawdown. Other metrics adjust explicitly for risk, including the Sharpe ratio, Sortino ratio, alpha based on several risk-factor models, and various forms of manipulation-proof performance measures.

Despite the fact that many hedge funds aim to generate positive absolute returns, the actual returns are highly variable over the years. Actual returns received by the average investor, as measured by money-weighted rates, are below reported compound average rates of return. This disparity is because for all their wealth and apparent sophistication, hedge fund investors tend to fall prey to the same behavioral biases as small investors, which leads them to buy high and sell low all too often. The period between 1998 and 2008 was particularly damaging to the hedge fund industry, with negative returns, elevated risk, and high fund mortality rates.

Although caution is advisable for buyers of hedge fund shares, investors can distinguish talented managers from the merely lucky by using refined performance measurement techniques. Recent studies find evidence of portfolio manager skill that persists over periods exceeding a year, so identifying top managers a priori may be feasible. Moreover, crippling diseconomies of scale in the industry detected by earlier studies are not present for more recent periods. Perhaps the best news is that hedge fund returns are not highly correlated with those of traditional portfolios, suggesting that this asset class may bring a substantial and enduring diversification benefit.

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Table 23.1 Hedge Fund Monthly Returns, by Category

This table lists hedge funds' arithmetic average monthly returns net of fees by fund category between January 1994 and March 2016. For comparison, the last three rows show the monthly returns for the Merrill Lynch 3-month U.S. T-bill Index, S&P 500 Index, and the Russell 2000 Index over the same period.

Hedge Fund Strategy	Average Monthly Return (%)
Convertible arbitrage	0.46
Dedicated short bias	0.19
Emerging markets	0.44
Equity market neutral	0.54
Event driven	0.71
Fixed income arbitrage	0.46
Fund of funds	0.18
Global macro	0.51
Long/short equity hedge	0.78
Managed futures	0.85
Multi-strategy	0.65
Options strategy	0.58
All Hedge Funds	**0.50**
Comparison Indexes	
Merrill Lynch U.S. T-bill Index	0.23
S&P 500 Index	0.81
Russell 2000 Index	0.82

Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Table 23.2 Hedge Fund Monthly Returns for Incubation and Subsequent Periods

This table compares hedge funds' arithmetic average monthly returns net of fees, by hedge fund category, for the first 18 months of return and the period starting with month 19.

	Average Monthly Return		
Hedge Fund Strategy	**All Months (%)**	**First 18 Months (%)**	**Months 19 and After (%)**
Convertible arbitrage	0.46	0.80	0.29
Dedicated short bias	0.19	0.66	0.02
Emerging markets	0.44	1.14	0.07
Equity market neutral	0.54	0.75	0.34
Event driven	0.71	1.24	0.47
Fixed income arbitrage	0.46	0.90	0.18
Fund of funds	0.18	0.50	−0.03
Global macro	0.51	0.89	0.30
Long/short equity hedge	0.78	1.38	0.40
Managed futures	0.85	3.90	0.29
Multi-strategy	0.65	0.88	0.49
Options strategy	0.58	0.66	0.50
All Hedge Funds	**0.50**	**1.06**	**0.23**

Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Table 23.3 Hedge Fund Post-Incubation-Period Monthly Returns for Live and Graveyard Subsamples

This table lists hedge funds' arithmetic average monthly returns net of fees, based on whether the hedge fund was in operation or defunct on March 31, 2016. The returns include only months after the assumed incubation period (i.e., month 19 and after).

	Live Subsample		Graveyard Subsample	
Hedge Fund Strategy	**Average Return (%)**	**n**	**Average Return (%)**	**n**
Convertible arbitrage	0.61	41	0.24	237
Dedicated short bias	0.24	5	0.00	50
Emerging markets	0.40	230	−0.03	711
Equity market neutral	0.45	120	0.32	540
Event driven	0.53	165	0.45	630
Fixed income arbitrage	0.43	114	0.10	353
Fund of funds	0.21	1,635	−0.12	4,626
Global macro	0.47	230	0.24	622
Long/short equity hedge	0.53	877	0.36	2,861
Managed futures	0.47	299	0.23	798
Multi-strategy	0.69	862	0.36	1,418
Options strategy	0.67	18	0.42	37
All Hedge Funds	**0.43**	**4,873**	**0.15**	**13,219**

Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Table 23.4 Comparison of Characteristics of Hedge Fund Monthly Return both Unwinsorized and Winsorized

This table lists hedge funds' arithmetic average monthly returns net of fees, unwinsorized and after being winsorized. In the winsorizing process, extreme returns below (above) percentile 1 (99) are fixed at those respective levels. The returns are measured only after the assumed incubation period (i.e., month 19 and after). The table also shows extreme values for each hedge fund category. For comparison, the last three rows provide monthly returns for the Merrill Lynch 3-month U.S. T-bill Index, S&P 500Index, and Russell 2000 Index over the same period.

Hedge Fund Strategy	Unwinsorized Monthly Returns						Winsorized Returns			
	Avg. (%)	Std. Dev. (%)	Skew.	Kurt.	Min. (%)	Max. (%)	Avg. (%)	Std. Dev. (%)	Skew.	Kurt.
Convertible arbitrage	0.29	0.71	−0.75	6.91	−87	108	0.31	0.67	−0.48	4.01
Dedicated short bias	0.02	1.28	0.36	2.68	−57	66	−0.12	0.94	0.19	0.32
Emerging markets	0.07	1.96	−0.39	4.25	−90	405	0.22	1.29	−0.24	1.53
Equity market neutral	0.34	3.97	−0.42	4.01	−100	6,625	0.24	1.00	−0.36	2.55
Event driven	0.47	1.25	−0.48	4.28	−65	184	0.46	1.09	−0.44	3.03
Fixed income arbitrage	0.18	1.16	−1.01	8.38	−77	123	0.29	0.88	−0.70	5.02
Fund of funds	−0.03	1.55	−0.82	4.53	−97	1,471	0.02	0.95	−0.74	3.05
Global macro	0.30	1.33	0.06	2.72	−100	213	0.30	0.95	0.03	1.75
Long/short equity hedge	0.40	3.13	−0.14	2.59	−99	9,718	0.36	1.13	−0.15	1.15
Managed futures	0.29	1.32	0.06	2.88	−100	58,742	0.28	1.02	−0.03	1.34
Multi-strategy	0.49	7.34	−0.47	5.32	−100	13,951	0.39	1.09	−0.39	3.85
Options strategy	0.50	1.45	−0.58	7.58	−61	41	0.56	1.17	−0.54	5.66
All Hedge Funds	**0.23**	**3.30**	**−0.48**	**4.21**	**−100**	**58,742**	**0.23**	**1.05**	**−0.43**	**2.62**
Comparison Indexes										
Merrill Lynch U.S. T-bill Index	0.23	0.19	0.15	−1.56	0	1				
S&P 500 Index	0.81	4.30	−0.66	1.10	−17	11				
Russell 2000 Index	0.82	5.58	−0.50	1.06	−21	17				

Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Table 23.5 Other Common Performance Metrics for Hedge Funds

This table lists several common performance measures for hedge funds based on monthly returns (unwinsorized) and reported by hedge fund strategy. The first column shows the average percent of months in which the hedge funds have positive returns. The second column shows the average for hedge funds' greatest percent decline in per share value from a previous maximum level. The third column contains the Sharpe ratio, where the risk-free rate is the 3-month U.S. T-bill rate. The Sortino ratio is in the final column. For comparison, the last three rows provide monthly returns for the Merrill Lynch 3-month U.S. T-bill Index, S&P 500 Index, and Russell 2000 Index over the same period.

Hedge Fund Strategy	Months Positive (%)	Maximum Drawdown (%)	Sharpe Ratio	Sortino Ratio
Convertible arbitrage	69	−19	0.21	0.36
Dedicated short bias	51	−40	0.07	0.16
Emerging markets	59	−38	0.12	0.21
Equity market neutral	62	−17	0.15	0.28
Event driven	68	−21	0.24	0.45
Fixed income arbitrage	74	−17	0.57	1.05
Fund of funds	61	−21	0.25	0.64
Global macro	61	−19	0.29	0.53
Long/short equity hedge	59	−27	0.14	0.30
Managed futures	55	−27	0.09	0.21
Multi-strategy	72	−17	0.60	1.04
Options strategy	68	−18	0.24	0.35
All Hedge Funds	**61**	**−23**	**0.28**	**0.41**
Comparison Indexes				
Merrill Lynch U.S. T-bill Index	97	− 0	0.00	0.00
S&P 500 Index	64	−51	0.14	0.18
Russell 2000 Index	60	−53	0.11	0.15

Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Table 23.6 Hedge Fund Alphas Based on Four Models

This table lists hedge funds' market model betas and monthly alphas based on the market model (MM), Fama-French three-factor model, Carhart four-factor model, and Fung-Hsieh seven-factor model. Emerging market funds only are evaluated using the Fung-Hsieh eight-factor model. All model parameters are generated based on unwinsorized returns.

Hedge Fund Strategy	MM Beta	MM Alpha (%)	Fama-French Alpha (%)	Carhart Alpha (%)	Fung-Hsieh Alpha (%)
Convertible arbitrage	0.17	0.11	0.10	0.13	0.15
Dedicated short bias	−0.67	0.07	0.08	0.07	0.20
Emerging markets	0.54	−0.19	−0.22	−0.21	−0.03*
Equity market neutral	0.10	0.11	0.07	0.06	0.09
Event driven	0.28	0.20	0.16	0.17	0.22
Fixed income arbitrage	0.12	0.18	0.16	0.17	0.17
Fund of funds	0.22	−0.15	−0.17	−0.18	−0.13
Global macro	0.11	0.24	0.21	0.18	0.27
Long/short equity hedge	0.49	0.22	0.22	0.18	0.27
Managed futures	0.04	0.19	0.14	0.11	0.13
Multi-strategy	0.12	0.39	0.37	0.37	0.39
Options strategy	0.13	0.27	0.24	0.22	0.31
All Hedge Funds	**0.25**	**0.09**	**0.07**	**0.06**	**0.12**

* Alpha from the eight-factor model includes an emerging markets risk factor.
Sources: Thomson Reuters' Lipper Hedge Fund Database (2016) and the websites of David Hsieh and Kenneth French.

Table 23.7 Hedge Fund Performance Based on Fund Size

This table shows raw monthly returns (Panel A) and Fung and Hsieh seven-factor model monthly average alphas (Panel B) between April 2011 and March 2016, based on each fund's March 31, 2011 decile of AUM. Emerging market funds only are evaluated using the Fung-Hsieh eight-factor model. Panel C shows percentiles of the distribution of hedge fund AUM on March 31, 2011 and December 31, 2015. This table uses unwinsorized returns.

Hedge Fund Strategy	All Funds (%)	Emerging Markets (%)	Fund of Funds (%)	Long/Short Equity Hedge (%)	Multi-Strategy (%)
Panel A. Monthly Return					
Largest quintile	0.46	−0.38	0.39	0.19	1.20
Smallest quintile	0.14	−0.25	−0.78	0.13	1.55
Difference	0.33	−0.13	1.17	0.06	−0.36
Panel B, Fung-Hsieh Monthly Excess Return					
Largest quintile	0.27	0.48	0.57	0.49	1.31
Smallest quintile	0.08	0.06	−0.45	0.73	0.71
Difference	0.19	0.42	1.02	−0.24	0.60

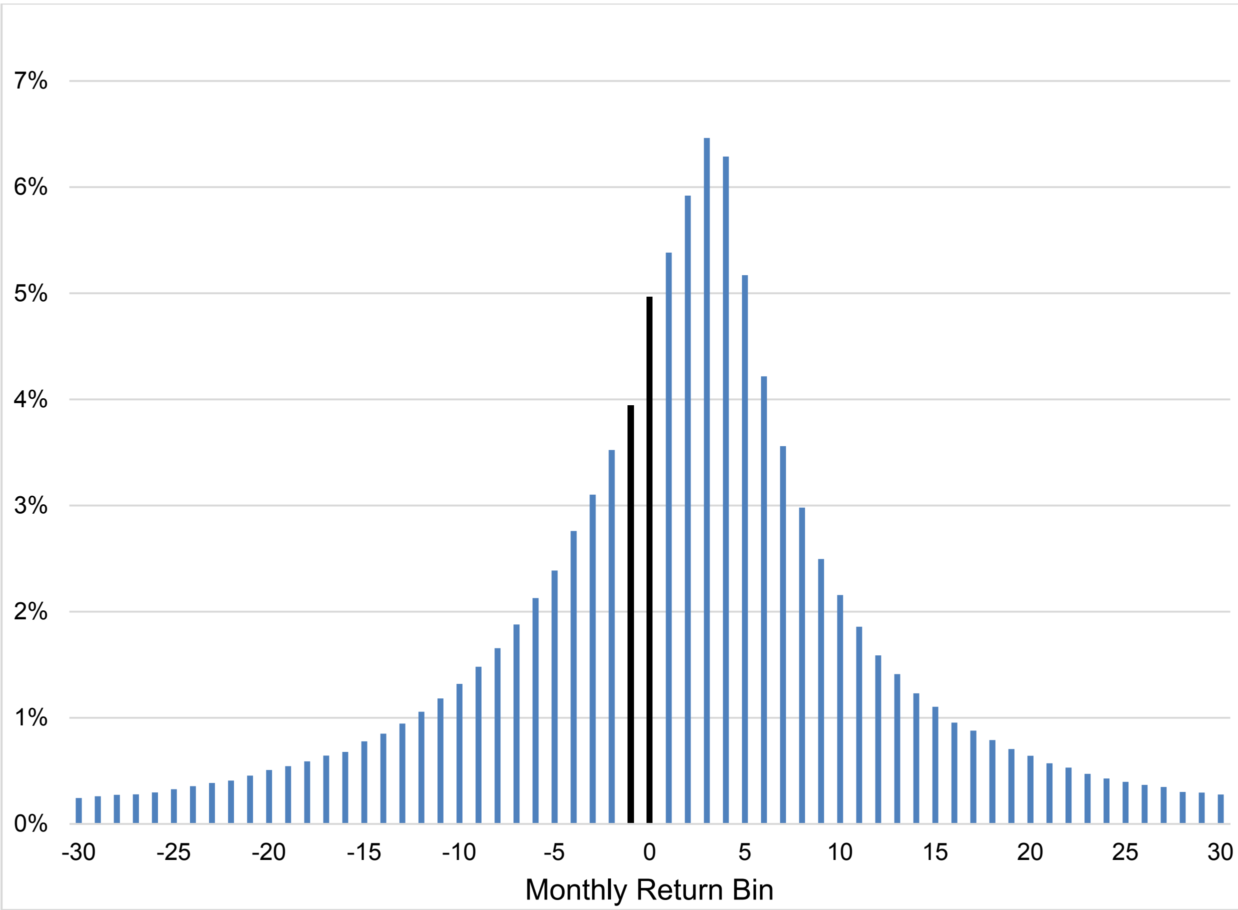
Panel C. Distribution of Hedge Fund AUM

Percentile	March 31, 2011	December 31, 2015
10	$3,480,318	$3,790,215
20	$8,769,957	$7,904,741
25	$12,330,010	$10,285,500
30	$16,894,129	$13,658,738
40	$26,900,134	$21,113,736
50	$42,954,615	$33,969,500
60	$68,121,456	$53,223,362
70	$117,568,203	$89,240,000
75	$149,959,563	$118,433,600
80	$208,304,980	$163,000,000
90	$456,201,160	$405,185,891
100	$51,364,494,646	$51,349,000,000

Sources: Thomson Reuters' Lipper Hedge Fund Database (2016) and David Hsieh's website.

Figure 23.1 Distribution of Reported Monthly Hedge Fund Returns

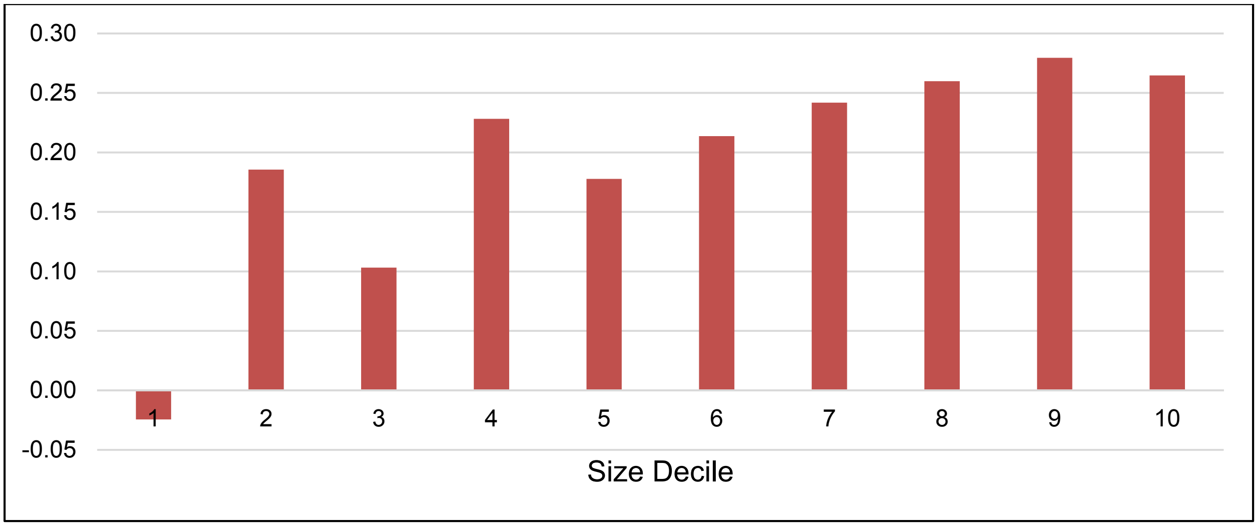
This figure shows the relative frequencies of monthly reported returns (unwinsorized) for all hedge funds between April 1, 1994 and March 31, 2016. The graph is centered over zero percent and presents 30 bins above and below zero. Each bin is 20 basis points wide, consistent with Figure 2b in Bollen and Pool (2009). The bold vertical bars bracket zero.



Source: Thomson Reuters' Lipper Hedge Fund Database (2016).

Figure 23.2 Association Between Hedge Fund Size and Performance.

This figure shows Fung and Hsieh seven-factor model monthly average alphas between April 2011 and March 2016 based on each fund's March 31, 2011 decile of AUM. Emerging market funds only are evaluated using the Fung-Hsieh eight-factor model. Alphas are in percent and are generated using unwinsorized returns.



Sources: Thomson Reuters' Lipper Hedge Fund Database (2016) and Prof. David Hsieh's website.