CHAPTER 1

Fund Selection and Data Envelopment Analysis

INTRODUCTION

Since Alfred Winslow Jones created the first hedge fund in 1949, the hedge fund universe has grown to comprise nearly 7,000 funds, in addition to approximately 750 funds of hedge funds (baskets of hedge funds). The popularity of alternative assets like hedge funds and managed futures can be explained by their diversification capacity, which investors have become especially interested in since the market crash of October 1987. Because of their low or even negative correlation to stock and bond markets, hedge funds and managed futures are considered the best instruments for protecting investor capital while providing absolute returns (Schneeweis and Spurgin, 1998).

The lackluster performance of traditional asset classes over the last few years has encouraged many high–net worth individuals, pension funds, companies, investment banks, and endowments to commit more to alternative investments to improve overall returns and simultaneously reduce risk exposure during increased market turmoil. This emerging investment arena can also provide entrance to the more dynamic and lucrative global futures markets.

Hedge funds and managed futures differ from asset classes such as mutual funds because they are not affected by market movements. This is important for investors, because *the risk of a particular investment can be reduced and performance increased by combining uncorrelated securities in various asset classes* (Markowitz, 1952). Most hedge funds are limited to a maximum of 100 investors and are unregulated by the Securities Exchange Commission (SEC) because they are directed to sophisticated and high–net worth investors. Hedge funds can assume both long and short positions and buy undervalued and short overvalued securities in virtually any stock market. There are approximately a dozen various hedge fund strategies and a handful of managed futures classifications, each of which provides varying levels of return and risk, but all aim to reduce volatility in turbulent markets while delivering absolute returns under any market conditions.

However, performance measurement of hedge funds that use standard market indices as benchmarks has been problematic, since their very nature is alien to that of stock and bond funds. Hedge funds have nonlinear returns due to long/short positions, derivatives, and option-like fee contracts resulting in significant skewness and kurtosis (Agarwal and Naik, 2004; Fung and Hsieh, 1997, 1999; Liang, 2003). So the inclusion of hedge funds in investor portfolios calls for appraisal methodologies that are appropriate for handling the asymmetrical returns they produce. This is even more important given that hedge fund manager selection is a precise process for appraising both risk and reward.

Some benchmarks may be easier for hedge fund managers and commodity trading advisors (CTAs) to outperform because of the large number of funds making up the indices; this provides managers with an opportunity to add value (Wander, 2003, p. 54). Hedge funds and CTAs can outperform traditional long-only indices because they make use of dynamic trading strategies, derivatives strategies, short selling, and leverage to magnify returns.

The growth of CTAs has somewhat mirrored the growth of hedge funds. A CTA is a person or a firm that buys or sells commodity futures or options contracts for profit on various world markets. CTAs also provide advice indirectly to others on these activities. CTAs must be registered with the Commodity Futures Trading Commission (CFTC), and are required to adhere to disclosure and reporting rules and to maintain appropriate records. CTAs trade a variety of futures and indices, with the main areas consisting of currencies, commodities, equities, and fixed income.

CTAs now manage approximately $120 billion. The majority are trend-followers, and generate earnings by identifying trends in global markets. They use proprietary trading systems and generally experience lower maximum drawdowns in negative S&P 500 months and in extreme negative market events than the average equity mutual fund (Gregoriou and Rouah 2004).

Edwards and Caglayan (2001) note that CTAs tend to outperform hedge funds in bear markets and underperform them in bull markets. They achieve this through the use of strategies and derivative instruments such as short-selling, options, and futures, coupled with leverage to magnify returns. Several academic studies have argued that the optimal allocation of hedge funds and/or CTAs in traditional stock and bond portfolios should be approximately 10 to 20% (Karavas, 2000; Kat, 2004; Popova et al., 2003; Cvitanic et al., 2002). With this in mind, sophisticated investors and pension funds are slowly increasing their exposure to alternative investments from 5% to 10–15% for downside equity risk management (Schneeweis, Spurgin, and Potter 1996; Capocci and Hübner, 2003).

According to a recent report by the Barclay Trading Group (2003), managed futures grew by nearly 30% during 2003. An older report by JP Morgan (1994) concludes that allocating 15% or more to managed futures in traditional stock and bond investment portfolios would significantly reduce risk and increase return. In addition, a Chicago Mercantile Exchange study (1999) concluded that portfolios containing 20% managed futures yield up to 50% more returns with the same amount of risk than stock and bond portfolios. The Chicago Board of Trade (2003) concluded that a portfolio with the greatest returns and the least amount of risk consisted of 45% stocks, 35% bonds, and 20% managed futures. Including managed futures in traditional stock and bond portfolios creates an effect of diminishing the standard deviation at a faster rate than hedge funds can, without the unwanted symptoms of skewness and kurtosis as stated by Kat (2004, p. 5). However, it is important to keep in mind when adding hedge funds to traditional investment portfolios that they are likely to increase kurtosis and negative skewness because of the abnormality of their returns (Fung and Hsieh, 1997): the main drawback of this alternative asset class. Hedge funds also display fat tails, which reflects a greater number of extreme events than one would normally anticipate (Fung and Hsieh, 2000).

This book compares hedge fund and CTA performance using the alternative measure of Data Envelopment Analysis (DEA). DEA is a versatile method that uses multiple inputs and multiple outputs to assess hedge fund and CTA returns, thereby avoiding the problems inherent in using traditional passive and active benchmarks. DEA lends itself naturally to assessing the relative performance of hedge funds by making it possible to measure a hedge fund's efficiency relative to the best-performing hedge fund. This allows us to identify the driving factors that determine the efficiency of hedge funds, funds of hedge funds, and CTAs.

With the recent rise in studies investigating hedge fund (Capocci and Hübner, 2003) and CTA performance (Kat, 2004; Martellini and Vaissié, 2004; Hübner and Papageorgiou, 2004; Capocci, 2004), DEA is the perfect complementary technique to examine the efficiency of fund manager selection. Furthermore, the various DEA models used throughout this book can be used as guides for investors to examine potential funds for their portfolios.

FUND SELECTION

The process of identifying the best hedge fund managers through complex research is an art. Manager selection, or due diligence, is based on the fact that superior hedge fund managers can be identified because they generally display good stock selection abilities under a variety of different economic conditions (Gregoriou, Rouah, and Sedzro, 2002; Anson, 2000). However, the selection process requires assessment of both qualitative and quantitative characteristics. It is important to note that investment in alternative asset classes can greatly enhance returns, but if the manager selection process is performed incorrectly, these returns are likely to be mitigated.

Performance measurement is an important piece of the process that should not be neglected. The use of mean-variance portfolio analysis using computer spreadsheet optimizers is widespread, but there are many problems with such numerical algorithms. Selecting and constructing a fund of hedge funds is difficult. However, we find that by simply using user-friendly menus to obtain various statistics, it is possible to create a simulated FOF or even a group of CTAs with high historical returns, low volatility, and low correlation to the markets.

As noted, comparing hedge funds and CTAs to the various passive or active indices may result in incorrect performance assessment. Their dynamic nature makes comparison with passive long-only and active benchmarks problematic. The hedge fund manager and CTA selection process is actually more complex than it appears because of the nonnormality of hedge fund and CTA returns. Although many studies have used the S&P 500 and other static market indices to examine hedge fund and CTA classifications, the results obtained may not be accurate (Gregoriou, Rouah, and Sedzro, 2002; Edwards and Caglayan, 2001).

A passive futures index is based on a buy-and-hold strategy that maintains long-only commodity investments; it cannot be used, however, as a benchmark for strategies that hold short positions or trade financial futures contracts (Schneeweis and Spurgin, 1997, p. 33). An active index tracks the dynamic strategies using a 12-month moving average trading rule encompassing 25 actively traded commodity and financial futures contracts (Schneeweis, Spurgin, and Georgiev, 2001, p. 3). Some active indices such as the Mount Lucas Management Index (MLM) provides a partial explanation of CTA returns; however, the tracking error between the MLM index and CTAs is considered quite sizeable (Schneeweis and Spurgin, 1997, p. 34). Both passive and active managed futures indices are not free from tracking error, and selecting appropriate benchmarks to evaluate CTAs is difficult (Schneeweis and Spurgin, 1997). The authors further suggest that CTA based indices may be the best option as benchmarks; however, month-to-month comparisons of the index returns display large inconsistency in some months.

With only traditional passive and active benchmarks, how can an investor or a FOF manager compare the performance of a hedge fund or a CTA? Recent studies have used active hedge fund and CTA indices, but the problem is compounded because the individual hedge fund and CTA indices are not really typical for each classification (Chatiras, 2004, pp. 1–2).

Several authors have also used multifactor models to examine hedge fund and CTA performance (Edwards and Caglayan, 2000; Schneeweis and Spurgin, 1997). Due to their nonnormal characteristics, it is difficult to find appropriate active benchmarks, and in some cases the use of traditional benchmarks has resulted in low R-squared values because hedge funds do not have stable exposure to market factors over time (Brealey and Kaplanis, 2001). Furthermore, hedge funds are absolute return vehicles. Their primary aim is to provide superior performance with low volatility in both bull and bear markets. More sophisticated appraisal techniques, such as data envelopment analysis (DEA), are needed.

DEA yields many advantages over traditional parametric techniques, because regression analysis approximates the efficiency of hedge funds and CTAs under investigation relative to the average performance. DEA can play an important and primordial role in hedge fund manager and CTA selection because it eliminates the cumbersome benchmark selection process and the need to use linear factor models, such as the Capital Asset Pricing Model.

WHAT IS DATA ENVELOPMENT ANALYSIS?

Data envelopment analysis (DEA) is a data-oriented approach for evaluating the performance of a set of peer entities called Decision making units (DMUs) whose performance is characterized by multiple measures/indicators. The definition of a DMU is generic and flexible. In our case, DMU refers to a CTA or a hedge fund. As noted in Cooper, Seiford, and Zhu (2004), recent years have seen a great variety of applications of DEA for use in evaluating the performances of many different kinds of entities engaged in many different activities in many different contexts in many different countries. These DEA applications have used DMUs of various forms to evaluate the performance of entities, such as hospitals, the wings of U.S. Air Force aircraft, universities, cities, courts, business firms, and others, including the performance of countries, regions, and so on.

Since DEA in its present form was first introduced in 1978, researchers in a number of fields have quickly recognized that it is an excellent and easily used methodology for modeling operational processes for performance evaluations. This has been accompanied by other developments. For example, in Zhu (2003), a number of DEA spreadsheet models that can be used in performance evaluation and benchmarking are developed. DEA's empirical orientation and the absence of a need for the numerous a priori assumptions that accompany other approaches (such as standard forms of statistical regression analysis) have resulted in its use in a number of studies involving efficient frontier estimation in the governmental and nonprofit sector, the regulated sector, and the private sector. Because it requires very few assumptions, DEA has opened up possibilities for use in cases that have been resistant to other approaches because of the complex (often unknown) nature of the relations between the multiple measures.

Figure 1.1 illustrates the basic concept of DEA and how DEA identifies the efficient frontier and establishes benchmarking standards. In Figure 1.1, the *x*-axis represents the standard deviation and *y*-axis represents the return.

Using linear programming technique, DEA identifies a piecewise linear efficient frontier—the solid line shown in Figure 1.1. No other observed DMUs have a better return-risk combination than those DMUs on the identified DEA efficient frontier. For DMU *D* who is termed as (DEA) inefficient, to improve its efficiency, its risk should be reduced to that of *D′* on the efficient frontier, or its return should be increased to that of *D″*. *D′* or *D″* then is identified as the benchmark for DMU *D*.

In DEA, multiple performance measures are called inputs and outputs. In Figure 1.1, the risk is a DEA input and the return is a DEA output. Usually, the inputs represent measures where smaller values are preferred (for

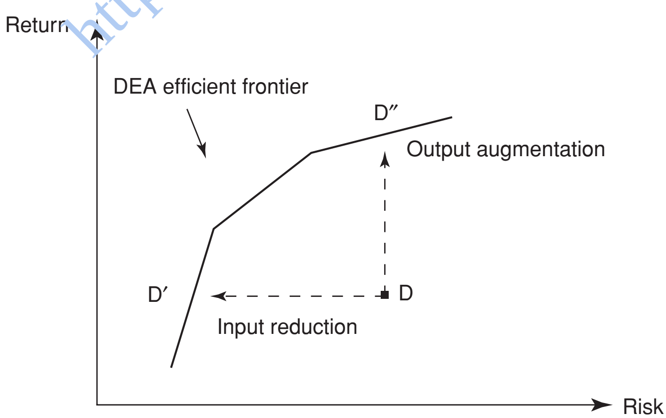

FIGURE 1.1 DEA Efficient Frontier

example, risk measures), and the outputs usually represent measures where larger values are preferred (for example, returns).

Figure 1.1 shows that DEA uses either input reduction or output increase for inefficient DMUs to reach the efficient frontier. The efficient frontier is composed by the DMUs where no input reduction and output increase are necessary. As a result, we have input-oriented DEA models where the inputs are optimized (reduced) while the outputs are kept at their current levels, and output-oriented DEA models where the outputs are optimized (increased) while the inputs are kept at their current levels. We illustrate these two types of DEA models using Figures 1.2 and 1.3.

Figure 1.2 shows five CTAs; each has the same return during one common time period. The two inputs are standard deviation and proportion of monthly negative return. In this example, CTA4 and CTA5 are relatively inefficient. For example, CTA4 has the same standard deviation as CTA2 but has 15% more negative monthly returns. DEA compares all five CTAs based upon the two inputs and the single output and identifies CTA1, CTA2, and CTA3 as the best-practice units. The efficient frontier is represented by the line segments between these three efficient CTAs. DEA identifies T1 on the line segment between CTA1 and CTA2 as the benchmarking standard for the inefficient CTA4.

Figure 1.3 shows five hedge funds HF1 through HF5, assuming they have the same input level (for example, same standard deviation). The two outputs are return and skewness. The output-oriented DEA identifies HF1, HF2, and HF3 as the best-practice units. HF4 and HF5 should increase

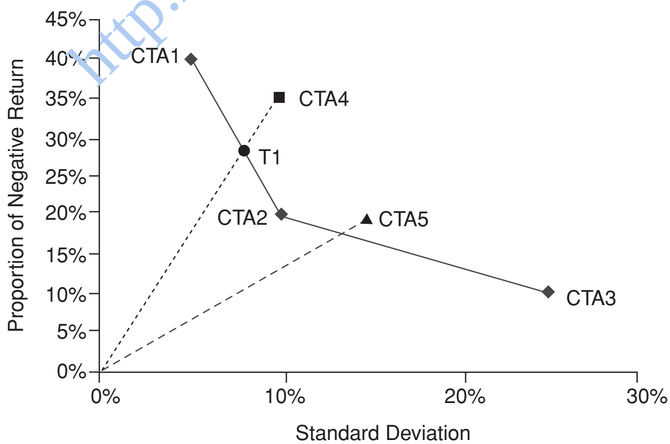

FIGURE 1.2 Input-Oriented DEA

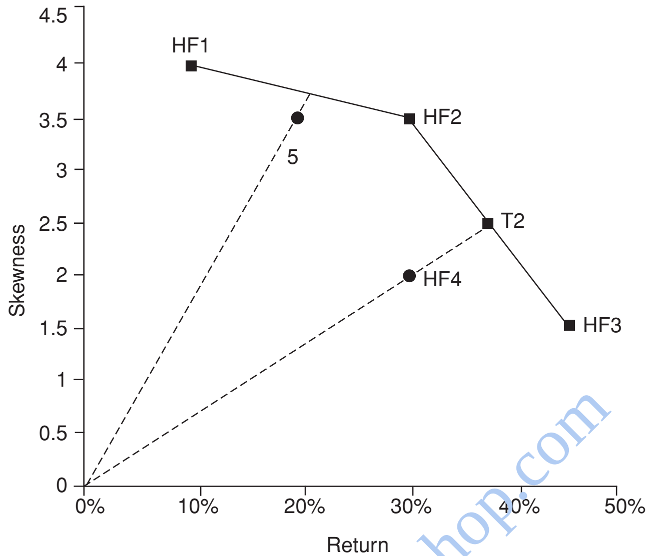

FIGURE 1.3 Output-Oriented DEA

their current output levels with the current amount of input. T2 is the benchmarking standard for HF4.

From this discussion, it can be seen that DEA uses the following definition to identify the efficient frontier (Cooper, Seiford, and Zhu, 2004).

> *Definition 1.1 (Relative Efficiency): A DMU is to be rated as efficient on the basis of available evidence if and only if the performances of other DMUs do not show that some of its inputs or outputs can be improved without worsening some of its other inputs or outputs.*

Cooper, Seiford, and Zhu (2004) point out that this definition avoids the need for recourse to prices or other assumptions of weights that are supposed to reflect the relative importance of the different inputs or outputs. It also avoids the need for explicitly specifying the formal relations that are supposed to exist between inputs and outputs with various types of models, such as linear and nonlinear regression models. This basic kind of efficiency, referred to as "technical efficiency" in economics can be extended, however, to other kinds of efficiency when data such as prices, unit costs, and so on, are available for use in DEA.

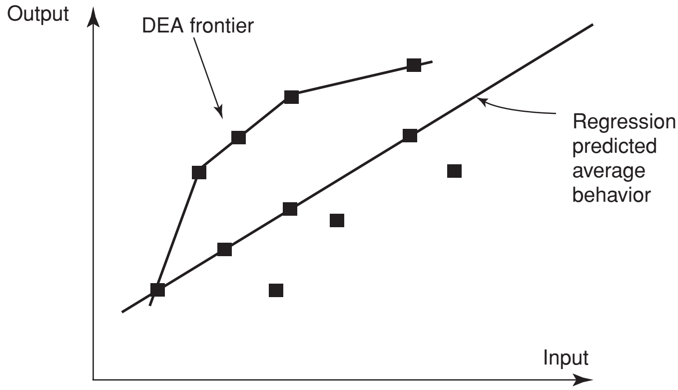

FIGURE 1.4 DEA and Regression

DEA is originally described as a “mathematical programming model applied to observational data [that] provides a new way of obtaining empirical estimates of relations—such as the production functions and/or efficient production possibility surfaces—that are cornerstones of modern economics” (Charnes, Cooper, and Rhodes, 1978). In fact, DEA is a methodology directed to frontiers rather than central tendencies. Instead of trying to fit a regression plane through the center of the data as in statistical regression, for example, one “floats” a piecewise linear surface to rest on top of the observations, as shown in Figure 1.4.

DEA provides basic benchmarking information that includes (1) an efficiency score for each DMU, (2) an efficiency reference set with peer DMUs, (3) a target for inefficient DMU, and (4) information detailing by how much inputs can be decreased or outputs can be increased to improve performance. As a result, we have an efficient frontier consisting of best-practice units and a projection to the frontier that can be used as a “what to do” guide for fund managers. The efficiency reference set is composed by efficient DMUs that are used to construct the target, or benchmarking standard, for inefficient DMUs (for example, the efficiency reference set for CTA5 in Figure 1.2 consists of CTA2 and CTA3). Therefore, DEA provides a fair benchmarking tool.