Selecting Top Decile Managers

Suppose we are considering a pool of 50 fund managers and want to select the best five managers to include in our asset allocation. Exhibit 1 displays the cumulative alphas of these 50 managers over a 60-month period. Also, assume that only one of these 50 managers has a true positive annual alpha of 2% with a tracking error of 6% per year. The other 49 managers have zero true alphas with the same tracking error of 6% per year.

What are the chances that one of the top 5 managers is the manager with a true positive alpha? The answer is less than 2%! This will surprise most asset allocators. After all, 60 months is a long period, and with our star manager generating 2% alpha with 6% tracking error, we would expect the star manager to be near the top, if not the top manager.¹

The problem is that while our manager’s alpha is significant at 99% level, we are comparing the manager’s performance to a highly biased sample – the managers who were lucky to produce positive
alphas while their true alphas were zero. If we compare our star manager’s performance to that of a randomly selected unskilled manager, there is about 99% chance that we identify our star manager (there will be about 1% chance that through pure luck a manager could match the performance of the star manager over a 60-month period). However, we are not comparing the star manager’s performance to that of a randomly selected manager here.

How could the probability that the star manager is among the top 5 managers from a pool of 50 managers be so low? To understand this, let’s look at the problem from a different perspective. Suppose all 50 managers have zero true alpha. What is the expected value of the cumulative alpha the top manager? The answer is 30%! That is, the luckiest manager is expected to produce about 6% alpha per year over a 5-year period. Of course, this manager is highly unlikely to repeat the same performance over the next five years, leading our asset allocator to regret his/her decision to hire the top manager. How about the average performance of the top 5 managers? The answer is about 3% alpha per year. That is, the average performance of the top 5 managers is higher than the average performance of our star manager, which is 2% per year. Again, the problem is that we are comparing our star manager to a highly biased sample of the managers. As discussed above, if we select a manager randomly and compare her performance to our star manager’s performance, there is 99% chance that we will identify our star manager, but the sample of the top 5 managers is not random. Exhibit 2 displays the same data from Exhibit 1, but this time, the path of the star manager’s alpha is highlighted.
How to Avoid the Dangers of Chasing Performance

The above analysis illustrates the dangers of chasing performance while not making adequate adjustments for the potential pitfalls of using highly biased samples. The above analysis applies to trading strategies, as well. In other words, we could evaluate the performances of 50 different trading strategies over a 60-month trial period. Even if every single strategy has zero true alpha, the top strategy is expected to have an alpha of 6% per year. By the way, the worse performing strategy is expected to show a negative alpha of 6% per year, even though all of them have zero true alphas.

What should an asset allocator do? One obvious answer is to use a longer track record. For example, we can use a pool of 50 managers with 20-year track records. There is a 90% chance that our star manager will be among the top 5 managers after 20 years. Of course, 20 years is a very long period, especially in the alternative investment industry. Also, note that the probability of selecting our star manager is still not 100%. To achieve that level of certainty, we need about 50 years of data.

There are four potential problems in finding a pool of managers with long track records. First, there will be significant survivorship bias in our sample because we are selecting managers that have been good, lucky, or both to survive 10 or 20 years. Second, in the hedge fund industry, a 5-year track record is actually rather long. So, finding a large pool of managers with track records exceeding five years is a difficult task. Third, most managers that have long attractive track records are likely to be closed to outside money. Finally, a fund manager with a long track record may not stick around for much longer, and, therefore, the investor faces the risk that the new manager may not be able to produce the same performance record.

Another potential solution to the problem is to focus on low volatility strategies. The primary reason that the probability of finding the star manager among the top 5 managers is so low is the volatility of the alphas. While 6% tracking error is typical for most active managers, the problem will become far less serious if we were to focus on strategies with low tracking errors. For example, continuing with our previous example, if the tracking error is 3% per year, then there is a 90% chance that our star manager will be among the top 5 performing managers. There is an important lesson here: since historical performances of the low volatility managers are more reliable, the investor can use quantitative approaches to due diligence in case of these managers. On the other hand, the investor should use qualitative approaches when evaluating managers in high volatility strategies as their track records are not highly reliable.

A final solution that I want to discuss is to focus on strategies where the relative number of skilled managers is expected to be large. This sounds rather obvious, but the implications of it may not be so obvious. The following example demonstrates the importance of focusing on the segment of the market where alpha is likely to be found, and in the process, we demonstrate an important application of Bayesian analysis.

In this example, we are examining a pool of managers, and after collecting their historical track records and calculating their alphas, we want to be confident that the selected manager has a true positive alpha. That is if the observed alpha is denoted by \( \bar{\alpha} \) and the true alpha by \( \alpha \), we want to know the
value of $P(\alpha > 0 \mid \bar{\alpha})$, the probability that the manager’s true alpha is positive given the historical value of its alpha.

Suppose we believe that some percentage of equity long/short hedge fund managers have true positive alphas. This probability is denoted by $P(\alpha > 0)$. For example, if $P(\alpha > 0) = 0.05$, it means that there is a 5% chance that a randomly selected manager is skilled. Therefore, 95% of managers have zero true alpha. Next, we collect a sample of performance record of a manager, estimate the manager’s historical alpha, and use an alpha detection method that has a very high degree of accuracy to tell us if the estimated alpha of the manager is consistent with a true positive alpha. This probability is given by $P(\bar{\alpha} \mid \alpha > 0)$. For instance, if $P(\bar{\alpha} \mid \alpha > 0) = 0.9$, then 90% of the times that a star manager’s historical record is analyzed, we correctly identify that manager and only 10% of the times we make a mistake and identify an unskilled manager as a star manager ($P(\bar{\alpha} \mid \alpha \leq 0) = 0.10$). Given these figures, what is the probability of observing a historical positive alpha?

$$P(\bar{\alpha}) = P(\bar{\alpha} \mid \alpha > 0) \times P(\alpha > 0) + P(\bar{\alpha} \mid \alpha \leq 0) \times P(\alpha \leq 0)$$

$$= 0.9 \times 0.05 + 0.1 \times 0.95 = 0.14$$

This means that 14% of the times we will observe a positive historical alpha – sometimes because a skilled manager’s track record is observed and sometimes because we are making a mistake and identify an unskilled manager as skilled. We are now ready to answer the most important question. Given a manager’s historical alpha, what is the probability that the manager’s true alpha is positive? That is, we want to calculate $P(\alpha > 0 \mid \bar{\alpha})$. Bayesian analysis can give us the answer:

$$P(\alpha > 0 \mid \bar{\alpha}) = \frac{P(\bar{\alpha} \mid \alpha > 0) \times P(\alpha > 0)}{P(\bar{\alpha})}$$

$$= \frac{0.9 \times 0.05}{0.14} = 0.32$$

This means that if the historical alpha of a manager is positive, then there is only a 32% chance that the manager’s true alpha is positive, a rather disappointing result. Of course, this is much higher than a 5% chance that a randomly selected manager is truly skilled, but it is still too low.

Next, consider the same example, but this time, we are looking at a strategy that 10% of managers have true positive alphas. That is, $P(\alpha > 0) = 0.1$. We keep the other figures the same. The results are

$$P(\bar{\alpha}) = P(\bar{\alpha} \mid \alpha > 0) \times P(\alpha > 0) + P(\bar{\alpha} \mid \alpha \leq 0) \times P(\alpha \leq 0)$$

$$= 0.9 \times 0.1 + 0.1 \times 0.9 = 0.18$$

Therefore,
In this case, 50% of the times we will select the skilled manager. If we can improve our alpha detection methodology through the use of better models and more data, the results will improve drastically. For instance, if in the last example we improve the accuracy of our model to 95%, then $P(\alpha > |\bar{\alpha}|) = 0.67$. This means that if we select a manager with positive historical alpha, there is a 67% chance that the manager’s true alpha is positive.

There is one last improvement that we can make in our result: We can select a portfolio of managers. For instance, suppose ten managers report positive alphas, and we decide to select 5 of them after performing our qualitative due diligence. The probability of having at least one truly skilled manager among those five managers is 99.6%, and the probability of having at least three skilled managers among those five managers is about 90%. This is another, and less noticed benefit of diversification: the investor is far more likely to have at least a few star managers in a portfolio of managers.

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1 This probability is calculated using the distribution of the order statistics. For example, see David and Nagaraja, “Order Statistics,” 3rd Edition, 2003, Wiley.