

A Markov Test for Alpha

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Abstract. Alpha is the amount by which the returns from a given asset exceed the returns from the wider market. The standard way of estimating alpha is to correct for correlation with the market by regressing the asset's returns against the market returns over an extended period of time and then apply the t -test to the intercept. The difficulty is that the residuals often fail to satisfy independence and normality; in fact, portfolio managers may have an incentive to employ strategies whose residuals depart *by design* from independence and normality. To address these problems we propose a robust test for alpha based on the Markov inequality. Since it based on the compound value of the estimated excess returns, we call it the *compound alpha test* (CAT). Unlike the t -test, our test places no restrictions of returns while retaining substantial statistical power. The method is illustrated on the distribution for three assets: a stock, a hedge fund, and a fabricated fund that is deliberately designed to fool standard tests of significance.

1. Testing for alpha

An asset that consistently delivers higher returns than a broad-based market portfolio is said to have *positive alpha*. Alpha is the mean excess return that results from the asset manager's superior skill in exploiting arbitrage opportunities and judging the risks and rewards associated with various investments. How can investors (and statisticians) tell from historical data whether a given asset actually is generating positive alpha relative to the market? To answer this question one must address four issues: i) multiplicity; ii) trends; iii) cross-sectional correlation; iv) robustness. We begin by reviewing standard adjustments for the first three; this will set the stage for our approach to the robustness issue, which involves a novel application of the Markov inequality.

The first step in evaluating the historical performance of a financial asset requires adjusting for multiplicity. Assets are seldom considered in isolation: investors can choose among hundreds or thousands of stocks, bonds, mutual funds, hedge funds, and other financial products. Without adjusting for multiplicity, statistical tests of significance can be seriously misleading. To take a trivial example, if we were to test individually whether each of 100 mutual funds "beats the market" at level $p = 0.05$, we would expect to find five statistically significant p -values when in fact *none* of them beats the market.

The literature on multiple comparisons includes a wide variety of procedures to correct for multiplicity. The simplest and most easily used of these is the Bonferroni rule. When testing m hypotheses simultaneously, one compares the

observed p -values to an appropriately reduced threshold. For example, instead of comparing each p -value p_i to a threshold such as $p = 0.05$, one would compare them to the reduced threshold p/m .

Modern alternatives to Bonferroni have extended it in two directions. The first, called alpha spending, allows the splitting of the alpha into uneven pieces; see for example Pocock (1977) and O'Brien and Fleming (1979). The second group of extensions provides more power when several different hypotheses are being tested. These can be motivated from many perspectives: false discovery rate (Benjamini and Hochberg 1995), Bayesian (George and Foster, 2000), information theory (Stine, 2004) and frequentist risk (Abramovich, Benjamini, Donoho, and Johnstone, 2006). One can even apply several of these approaches simultaneously (Foster and Stine, 2007). In the case of financial markets, however, the natural null hypothesis is that *no* asset can beat the market for an extended period of time because this would create exploitable arbitrage opportunities. Thus, in this setting, the key issue is whether *anything* beats the market, let alone whether multiple assets beat the market.

A second key issue in evaluating the historical performance of different assets is the need to de-trend the data. This is particularly important for financial assets, which generally exhibit a strong upward trend due to compounding. Consider, for example, the price series shown in Figure 1 for three different types of assets that span several different time periods.

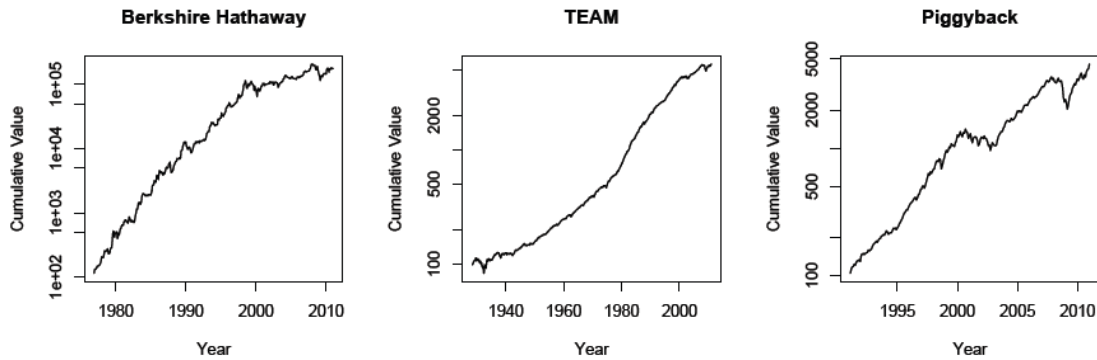


Figure 1. Value of three assets observed monthly over different time periods.

Berkshire Hathaway is a stock that is famous for its superior performance over a long period of time. TEAM is a fund that is based on a dynamic rebalancing algorithm which seeks to reduce volatility while maintaining high returns (Gerth, 1999; see also Agnew, 2002). This fund is especially interesting because (unlike many other hedge funds) its rebalancing strategy is explicit and its holdings are transparent: one knows at all times what assets are contained in the portfolio. By contrast the Piggyback Fund is assumed to be entirely nontransparent (to its investors). The reason is that it is based on an options trading strategy that is designed to fool investors into believing that the fund manager is able to 'beat the market' when in fact he is manufacturing high current returns by hiding large potential losses in the tail of the distribution (Lo, 2001; Foster and Young, 2010).

The simplest way to de-trend such data is to study the period-by-period returns rather than the value of the asset itself. That is, instead of focusing on the value, V_t , one studies the sequence of returns $(V_t - V_{t-1})/V_{t-1}$ over successive time periods

t (see figure 2). The hope is that the returns are being generated by a process that is sufficiently stationary for standard statistical tests to be applied. As we shall see, this hope may not be well-founded given that financial portfolios are often managed in a way that produces highly nonstationary behavior by design.

The third issue, cross-sectional correlation, arises because returns on financial assets often exhibit a high degree of positive correlation. The standard way to deal with this problem is the Capital Asset Pricing Model (CAPM), which partitions the variation in asset returns into two orthogonal components: market risk, which is non-diversifiable and hence unavoidable, and idiosyncratic risk. By construction, idiosyncratic risk is orthogonal to market risk and measures the rewards and risks associated with a specific asset. It is the mean return on this idiosyncratic risk, known as *alpha*, that draws investors to specific stocks, mutual funds, and alternative investment vehicles such as hedge funds.

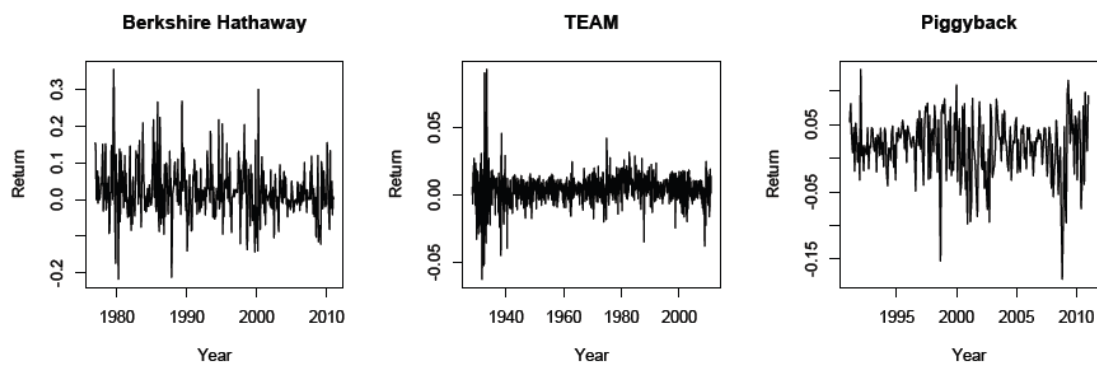


Figure 2. Monthly returns series for the three assets

The standard way to estimate the alpha of a particular asset or portfolio of assets such as a mutual fund is to regress its returns against the returns from a broad-

based market index such as the S&P 500 after subtracting out the risk-free return. Specifically, let the random variable M_t denote the return generated by the market portfolio in period t , and let r_t be the risk-free rate of return during the period, that is, the return available on a safe asset such as US Treasury Bills. The *excess return* of the market during the t^{th} period is $M_t - r_t$. Let Y_t^i denote the return in period t from a particular asset (or portfolio of assets) identified by the superscript i . The portfolio's *excess return* is defined as $Y_t^i - r_t$. CAPM posits that the excess return on each asset in the t^{th} period is a multiple of the excess return on the market plus a random term ε_t^i that has mean zero and is uncorrelated with the market excess returns, that is,

$$Y_t^i - r_t = \beta_t^i (M_t - r_t) + \varepsilon_t^i, \quad (1)$$

where

$$E[\varepsilon_t^i] = 0 \text{ and } E[\varepsilon_t^i (M_t - r_t)] = 0.$$

The coefficient β_t^i is the *beta* of the asset. Beta describes how returns on the asset co-vary with returns on the market as a whole, while ε_t^i is the *idiosyncratic risk* associated with the asset. A portfolio that leverages stocks has beta larger than 1, whereas a portfolio of bonds has beta approaching 0. Typically beta will vary over time as the portfolio manager changes his level of exposure to the market.

Let the random variable Y_t denote the return on a specific asset in time period t , where we drop the superscript i . The returns on the asset beat the market if in expectation ε_t^i is positive. If this is the case, an investor could increase his overall return by investing a portion of his wealth in this asset instead of in the market. Moreover, this increased return could be achieved without exposing

himself to much additional volatility, provided he puts a sufficiently small *proportion* of his wealth in the asset.

A second way in which an actively managed asset (such as a mutual fund) can beat the market is through market timing. Suppose that the manager invests a proportion p_t of its total wealth in the market at time t and leaves the rest in cash earning the risk-free rate r_t . The manager can adjust p_t depending on his belief about future market movements. If he expects the market to rise he might buy shares on margin, which corresponds to $p_t > 1$ and $\beta_t > 1$. If the manager expects the market to fall, he can short the market which implies that $p_t < 0$ and $\beta_t < 0$. A portfolio manager who successfully anticipates market movements is just as attractive as a manager who invests in assets which intrinsically have positive alpha. The asset labeled TEAM in figures 1 and 2 is an example of an actively managed portfolio in which the relative proportions allocated to cash and the market are rebalanced at the end of each period.

The standard way of estimating alpha is first to estimate the manager's level of exposure to the market at each point in time (β_t^i), and then to compute the mean of the residuals $\alpha = (1/T) \sum_{1 \leq t \leq T} \varepsilon_t^i$ as defined in (1). However, this fails to take successful market timing into account, which can be just as valuable as choosing specific investments. We therefore propose a generalization of alpha that incorporates skill in market timing as well as skill in choosing superior investments.

This concept is defined as follows. Given returns data for periods $t = 1, \dots, T$, let

$$\tilde{M}_t = M_t - r_t, \quad \tilde{Y}_t = Y_t - r_t. \quad (2)$$

Compute the means $\bar{\tilde{M}} = (1/T) \sum_{1 \leq t \leq T} \tilde{M}_t$ and $\bar{\tilde{Y}} = (1/T) \sum_{1 \leq t \leq T} \tilde{Y}_t$, and let

$$\beta = \frac{\sum_{1 \leq t \leq T} (\tilde{Y}_t - \bar{\tilde{Y}})(\tilde{M}_t - \bar{\tilde{M}})}{\sum_{1 \leq t \leq T} (\tilde{M}_t - \bar{\tilde{M}})^2}. \quad (3)$$

Thus β is the coefficient in the OLS regression of \tilde{Y} on \tilde{M}_t over the entire observation period.¹ We can then formally rewrite (1) as follows:

$$\tilde{Y}_t = \beta \tilde{M}_t + A_t, \quad \text{where } A_t = (\beta_t - \beta) \tilde{M}_t + \varepsilon_t. \quad (4)$$

The random variable A_t represents *generalized alpha*, which includes the returns from market timing and excess returns from the specific assets in the portfolio.

The standard way of conducting a test of significance would be to apply the t -test to the intercept in the regression specified in (4). However, the t -test presumes that the residuals A_t satisfy independence and normality, and there is no particular reason to think that these conditions hold in the present case. Indeed, when we graph the residuals from our three candidate assets over time, it

¹ We remark that β can also be interpreted as a weighted average of the period-by-period values β_t , weighted by the relative volatility of the asset in each period.

becomes apparent that two of them (Team and Piggyback) exhibit highly erratic, nonstationary behavior (see Figures 3-4) that renders the *t*-test completely inappropriate.

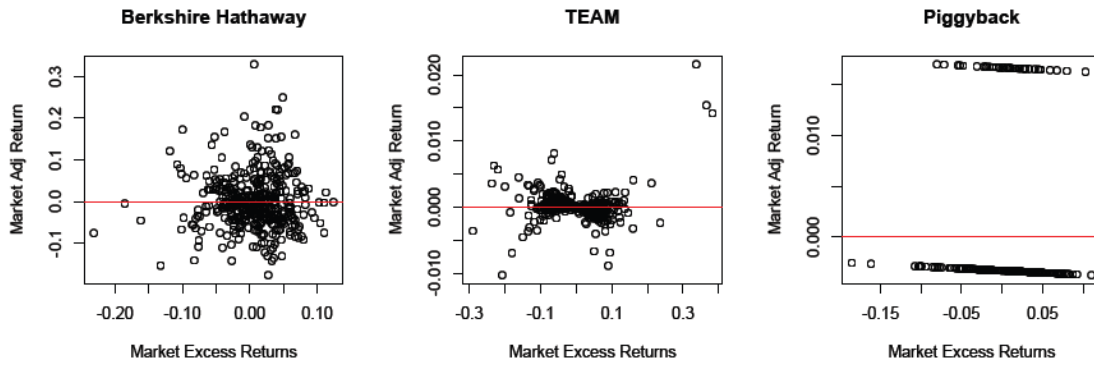


Figure 3. Market-adjusted returns versus market excess returns

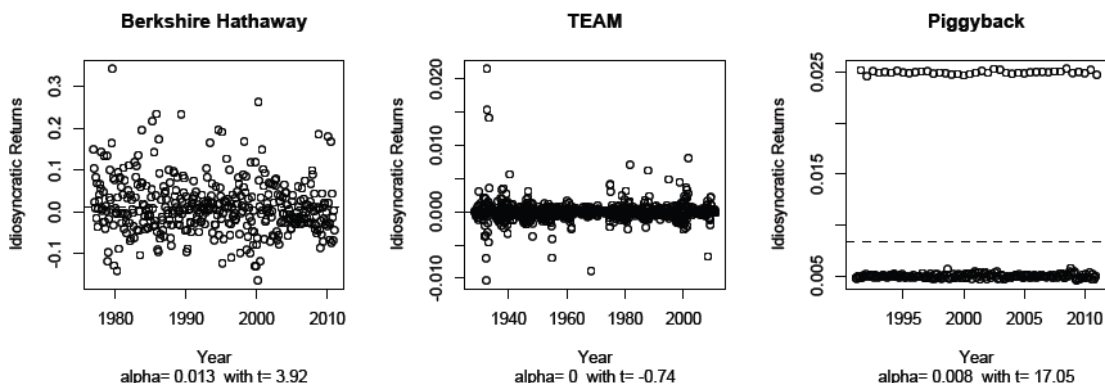


Figure 4. Time series of market-adjusted returns for the three assets.

In the case of Team, the market-adjusted returns exhibit a cyclic pattern with bursts of high volatility followed by periods of low volatility (see Figure 4), and residuals that have a peculiar ‘butterfly’ shape (see Figure 3). These features are direct consequence of Team’s dynamic rebalancing strategy. At any given time

the fund is invested in a mixture of cash (earning the risk-free rate of return) and the S&P 500. At the end of each period funds are moved from cash to stock if the risk-free rate in that period exceeded the market rate of return, and from stock to cash if the reverse was true. For purposes of illustration we chose the target proportions to be 20% stock, 80% cash, and rebalanced at the end of each 80-month period from May 1928 to December 2010. While this particular choice of targets does not produce especially high returns, it illustrates the point that the residuals from rebalancing strategies can be highly non-stationary.

The returns from the Piggyback Fund exhibit even more erratic behavior. The reasons for this will be discussed in section 3. Suffice it to say here that these returns are produced by a strategy that is designed to earn the portfolio manager a lot of money rather than to deliver superior returns to the investors. However, since the natural aim of portfolio managers *is* to earn large amounts of money, statistical tests of significance must accommodate this sort of behavior.

The purpose of this paper is to introduce a robust test for alpha that is immune to this and various other types of manipulation. The test is simple to compute and does not depend on the frequency of observations. A particularly important feature of the test is that it corrects for the possibility that the manager's strategy conceals a small risk of a large loss in the tail. This is not a hypothetical problem: empirical studies using multifactor risk analysis have shown that many hedge funds have negatively skewed returns and that as a result the *t*-test significantly underestimates the left-tail risk (Agarwal and Naik, 2004). Moreover, negatively skewed returns are to be *expected*, because standard compensation arrangements give managers an incentive to follow just such strategies (Foster and Young, 2010).

The plan of the paper is as follows. In section 2 we derive our test in its most basic form. The essential idea is to adjust the returns by first subtracting off the risk-free rate, then correcting for overall correlation with the market as in (3-4), and then compounding the residuals. We then apply the Markov inequality to test whether the compound value is growing, i.e. whether the final value is larger than the initial value with a high degree of confidence.

Section 3 shows why it is vital to have a test that is robust against erratic and nonstationary behavior of the residuals. In particular, we show that the t -test applied to the residuals leads to a false degree of confidence in the Piggyback Fund, which is constructed so that it looks like it produces positive alpha when this is not actually the case. In a second example we show why some other nonparametric tests, such as the martingale maximal inequality, are also inappropriate in this setting. The difficulty is that the fund manager can manipulate the degree of correlation with the market so that the *overall* degree of correlation is low, but in some periods the correlation is high. Thus the end value of the fund may not be impressive even though its interim value is large. This type of manipulation does not fool the Markov test, which is applied only to the final value of the fund, but it can fool the martingale maximal inequality, which is based on the maximum value achieved over the period.

In section 4 we show how to boost the statistical power of the test by leveraging the asset. First we show that if the returns of the asset are lognormally distributed with known variance, then we can choose a level of leverage such that the loss in power is quite low relative to the optimal test, which in this case

is the t -test. In fact, for a p -value of .01 the loss in power is less than 30%, and for a p -value of .001 the loss in power is only about 20%. We then show how to extend this approach to situations where we do not know the mean or variance of the asset in question. In this case we create a *hypothetical composite portfolio* such that each asset in the portfolio represents a different level of leverage applied to the original asset. We invest equal amounts in each of these hypothetical assets at the start of the observation period, compute the maximum final value of the portfolio at the end of the period, and apply our Markov test at a given level of significance. It can be shown that this leveraged version of the test is *asymptotically as powerful as the optimal test* when the returns are lognormally distributed, which is the standard assumption for many financial assets.

In section 5 we illustrate how our approach can be applied to data, focusing on the particular case of Berkshire. First we derive the market-adjusted monthly returns by subtracting off the risk-free rate and correcting for correlation with the market. Then we apply different amounts of leverage to these returns, taking into account the costs associated with higher levels of leverage (because of the need to insure that the fund does not go bankrupt in any given period). The resulting Berkshire p -value is quite impressive – about 0.00095. We need to consider, however, that we chose this stock precisely because it has been a stellar performer over a long period of time. If Berkshire is the best out of a population of 500 stocks, for example, then the Bonferroni correction would imply that the appropriate p -value is $(0.00095)500 = 0.475$, which is not significant. In other words, Berkshire considered by itself is very impressive, but out of a large population of stocks it is much less so.

2. The compound alpha test (CAT)

Consider a financial asset, such as a stock, a mutual fund, or a hedge fund whose performance we wish to compare with that of the market. The data consist of returns generated by the asset over a series of reporting periods $t=1,2,\dots,T$. Denote the market return in period t by the random variable M_t and the asset's return by the random variable Y . In applications, M_t would be the return on a broad-based portfolio of stocks such as the S&P 500 or the Wilshire 5000.

The first step in the analysis is to subtract off the risk-free rate of return in each period, that is, the rate available on a safe asset such as Treasury bills. In other words we define the random variables $\tilde{M}_t = M_t - r_t$ and $\tilde{Y}_t = Y_t - r_t$, where r_t denotes the risk-free rate in period t . The second step is to correct for correlation with the market over the entire period, that is, we compute the slope β from the OLS regression of \tilde{Y}_t on \tilde{M}_t as in (3). We then define the *market-adjusted return* in period t as follows

$$A_t = \tilde{Y}_t - \beta \tilde{M}_t. \quad (5)$$

Next we truncate the returns so that the total return $1 + A_t$ in each period is nonnegative. If the prices of \tilde{Y}_t and \tilde{M}_t evolve in continuous time with no jumps, this can be achieved by placing a stop-loss order on the market-adjusted asset $A_t = \tilde{Y}_t - \beta \tilde{M}_t$. In this case the truncated total return is simply $[1 + A_t]_+$.

An alternative approach is to insure the asset for the duration of the period using options. Assuming that $\beta > 0$, one buys a call option on the market that limits the risk from a large positive realization of \tilde{M}_t , and a put option on the asset that limits the risk of a large negative realization of \tilde{Y}_t . A crucial point is that, for ordinary financial assets such as publicly traded stocks and mutual funds, the cost of such insurance is very small when the time periods are short. (The reason is that the variance in returns of most assets scales in proportion to the length of the period.) Thus if the length of each period is sufficiently small, the probability that the returns will exceed a specified threshold is small, which implies that the price of insuring against such an event is small.²

To illustrate, suppose that $\beta = 0.5$ and that the length Δ of each period is one month. One can buy a call that protects against a rise of 67% or more in the market by the end of the month, and a put that protects against a fall of more than 67% in the price of the asset. This will guarantee that the market-adjusted asset cannot lose more than 100% of its value during the period, i.e., that $1 + A_t$ is nonnegative.³ The cost of such insurance will typically be very small because the probability of such an extreme move in one month's time is very remote; moreover it will be even more remote if we take the duration of the options to be even shorter, say one week. (In section 5 we estimate the monthly cost of insuring Berkshire Hathaway in this manner using empirical data on options prices.)

² For further details on options pricing see Hull (2009) or Campbell, Lo, and MacKinlay (1997).

³ The relative amount of protection in puts and calls can be chosen in many different ways to protect against a 100% drop in the market-adjusted asset. One would choose the cheapest such mixture based on the prices of the options.

Let Δ be the length of each period, and let $c_t = c_t(\Delta)$ represent the cost of insuring against negative realizations of the market-adjusted return $1 + A_t$ in period t . That is, at the start of the period we spend the fraction $c_t / (1 + c_t)$ of the portfolio on insuring the remainder of the portfolio ($1 / (1 + c_t)$) against bankruptcy by the end of the period. Thus the total return (net of insurance costs) is given by the nonnegative random variable

$$B_t = [1 + A_t]_+ / (1 + c_t). \quad (6)$$

(For notational convenience we omit the dependence on Δ .) Consider the compound value of the B_t 's over the T periods of observation:

$$C_T = \prod_{1 \leq t \leq T} B_t. \quad (7)$$

The *null hypothesis* is that $E[C_T] \leq 0$. Since B_t is a nonnegative random variable, the Markov inequality implies that this hypothesis can be rejected at significance level p if $C_T > 1/p$.

Compound Alpha Test (CAT). Let C_T be the compound market-adjusted return of a candidate asset through period T . The null hypothesis that the asset does not have positive alpha. This hypothesis can be rejected at significance level p if

$$C_T > 1/p. \quad (8)$$

Note that the compound value C_T must be very large before CAT rejects the null at a standard level of significance. For example, to reject the null at the 5% level of significance requires that the asset grow by *twenty-fold* after subtracting off the risk-free rate and correcting for correlation with the market.

Figure 5 shows the beta and compound value of the market-adjusted returns for each of our three candidate assets. Table 1 compares the p -values from our test with those from the t -test. According to the latter, Berkshire and Piggyback have positive alpha at a high level of significance and Piggyback is particularly impressive. By contrast, CAT says that we should only have confidence in Berkshire, and neither warrants the level of confidence that the t -test attributes to them.

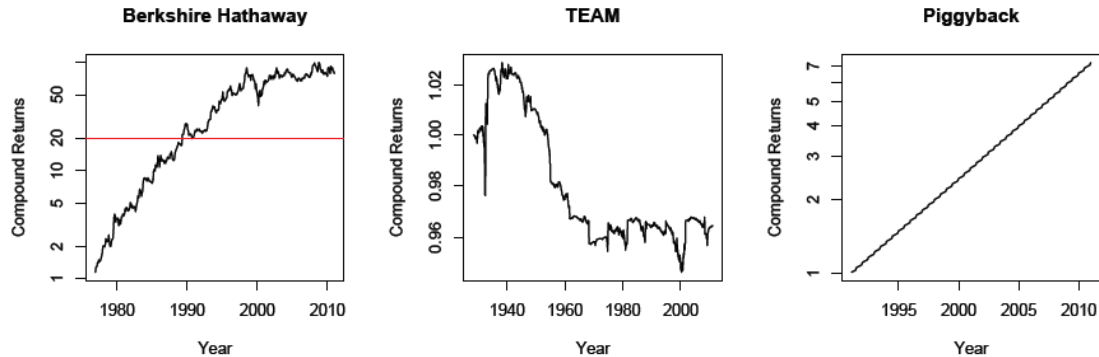


Figure 5. Compound value of market-adjusted returns for the three assets, not including the cost of insurance.

<i>Asset</i>	<i>Beta</i>	<i>Regression t</i>	<i>Regression p-value</i>	<i>CAT p-value</i>	<i>CAT "t"⁴</i>
Berkshire	0.67	3.92	0.00005	0.013	2.24
Team	0.20	-0.87	0.764	1.0	0
Piggyback	1.00	17.05	< 0.00001	0.14	1.09

Table 1. Regression p-values versus CAT p-values for the three assets.

3. Gaming the t-test.

At first it might seem counterintuitive that one would need to see a fund outperform the market by at least *twenty-fold* in order to be reasonably confident (at the 5% level of significance) that the superior performance is “for real.” The reason is that an apparently stellar performance can be driven by strategies that lead to a total loss with positive probability, but a very long time can elapse before the loss materializes. Indeed, it is easy to construct strategies of this nature for which the CAT p-value is tight. Choose a number $\gamma > 1$, and consider the following nonnegative martingale with conditional expectation 1

$$C_0 = 1, \quad P(C_t = \gamma^{1/T} C_{t-1}) = \gamma^{-1/T}, \quad P(C_t = 0) = 1 - \gamma^{-1/T} \text{ for } 1 \leq t \leq T. \quad (9)$$

In each period the fund compounds by the factor $\gamma^{1/T}$ with probability $\gamma^{-1/T}$ and crashes with probability $1 - \gamma^{-1/T}$. Thus the probability that the fund’s compound excess return C_t exceeds γ is precisely $1/\gamma$ over any number of periods T .

⁴ CAT “t” is the value of the *t*-statistic that corresponds to the given *p*-value using the normal distribution rather than a *t*-distribution.

Returns series with this property can be constructed using standard options contracts (Foster and Young, 2010).

The Piggyback Fund is constructed along just these lines. Namely, the fund is invested in the *S&P 500*, and the returns are reported every month. However, once every six months the total return is artificially boosted by the factor 1.02. This can be done by taking an options position in the S&P 500 that bankrupts the fund if the options are exercised. The strike price is chosen so that the probability of this event is $1/1.02 = .9804$, so the fair value of the option is zero. With probability $1/1.02$ the fund grows by the factor 1.02 and with probability $.02/1.02$ it loses everything, which is a lottery with expectation zero. This strategy explains the bizarre pattern of the market-adjusted residuals in Figure 3: one-sixth of the time they are +2%, and five-sixths of the time they are -2%. With less than 25 years of data there is a sizable probability that the downside risk will never be realized, and investors will be lulled into thinking that the fund is generating positive alpha. Because it guards against this possibly unobserved volatility, *CAT* attaches a modest *p*-value to the returns generated by the Piggyback Fund.

Of course, even a casual inspection of the residuals in Figures 3-4 suggests that the *t*-test should not be used in this case. However this is not the essence of the problem, because it is easy to construct similar strategies whose returns look i.i.d. normal. For instance, suppose that every month the manager boosts the fund's returns by the factor 1.0033λ where λ is a lognormally distributed error with mean 1 and small variance. (The purpose of the variation is to lend plausible variability to the realized returns.) As before, the boost comes at the cost of

going bankrupt with probability $1/(1.0033\lambda) \approx .9967/\lambda$ each month. Assuming that the variance of λ is small, this scheme will run for about 300 months (25 years) before the fund goes bankrupt, and the residuals will look very convincing. Thus, in this case the t -test would seem to be appropriate, and the estimate of alpha will be about 4% per year at a very high level of significance. This is misleading, however, because in reality the distribution of returns is not approximately normal -- there is a large potential loss hidden in the tail. One of the main virtues of our test is that it corrects for this "hidden volatility": after 25 years the p -value of this scheme will only be about $p = (1.0033)^{-300} \approx .37$.

A different manipulation based on market timing requires that CAT rely on the final cumulative return after a fixed test period rather than, say, using the maximum return over $t = 1, \dots, T$. The idea of this manipulation is to disguise a highly leveraged market position as an asset whose overall $\beta = 0$. For instance, one can obtain such an asset by leveraging the market to obtain the returns $\tilde{Y}_t = 2\tilde{M}_t$ for $t = 1, \dots, T/2$. For the remainder of the test period, one would short the market so that the returns are $\tilde{Y}_t = -2\tilde{M}_t$ for $t = T/2, \dots, T$. By construction, $\beta = 0$ and $A_t = \tilde{Y}_t$. Given the generally positive returns produced by the US stock market, the intermediate cumulative return is very likely to exceed an impressive threshold.

To illustrate, Figure 6 tracks the compounded monthly returns from a fund that leveraged the market by a factor of 2 from January 1926 to June 1968, then leveraged it by a factor of -2 from July 1968 to December 2010. By mid-1968 the fund's value has grown by a factor of 226. If the null hypothesis is that the market-adjusted returns form a martingale, then by the martingale maximal

inequality we would reject the null at significance level $1/226 = 0.0044$. In reality, however, the fund has no positive alpha. The reason why the martingale maximal test is fooled is that the portfolio manager can manipulate the correlation with the market over the entire period, hence the market-adjusted returns do not in fact form a martingale.⁵

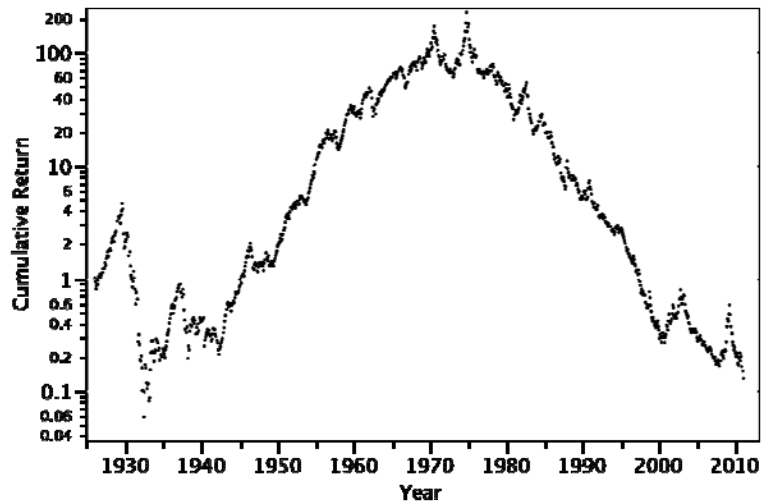


Figure 6. Cumulative returns of a portfolio in which the correlation with the market is manipulated .

4. Power and leverage

In this section we develop a more powerful variant of our test using leverage. To illustrate the approach, we shall first consider the special case in which the returns are i.i.d. lognormal with unknown mean and *known* variance. In this case the optimal test of significance is the *t*-test applied to the logged returns. We shall

⁵ The difficulty arises from the fact that the returns from the asset are adjusted for correlation with the market. If one is simply testing whether the returns from an asset are on average higher than the returns from the market (with no correction for β), then the martingale maximal inequality is an appropriate test (see Foster and Young, 2011).

show that by leveraging the asset at an appropriate level (which is determined by the variance), we obtain a generalization of our test that involves only a modest loss of power compared to the optimal test. Then we shall show that a similar result holds even when we do not know the variance.

To be concrete, consider a manager whose fund is generating compound returns $C_T > 0$ relative to the risk-free rate and suppose for simplicity that there is no correlation with the market ($\beta = 0$). Let us further assume that C_T is lognormally distributed:

$$\ln C_T \sim N((\mu - \sigma^2 / 2)T, \sigma^2 T). \quad (10)$$

This is consistent with the traditional representation of asset returns as a geometric Brownian motion in continuous time, that is, a stochastic differential equation of form $dC_t = \mu C_t dt + \sigma C_t dW_t$ (Berndt, 1996; Campbell, Lo, and MacKinlay, 1997). When the asset is leveraged by the factor $\lambda > 0$,⁶ the log of the compound returns at time T , $C_T(\lambda)$, are normally distributed:

$$\ln C_T(\lambda) \sim N((\lambda\mu - \lambda^2\sigma^2 / 2)T, \lambda^2\sigma^2 T). \quad (11)$$

Suppose, for the moment, that σ^2 is known and μ is not. The *null hypothesis* is that $\mu = 0$ and the *alternative hypothesis* is that $\mu > 0$. Choose a level of

⁶ To leverage an asset which sells for \$1 by the factor λ one borrows $\lambda - 1$ dollars at the risk-free rate and invests λ dollars in the asset. If $\lambda < 1$ this means that $1 - \lambda$ is invested in the risk-free asset and the remainder in the risky asset. Notice that to keep a constant level of leverage at all times one needs to rebalance the absolute amounts invested in each asset. In continuous time this yields the process $dC_t = \lambda\mu C_t dt + \lambda\sigma C_t dW_t$.

significance $p > 0$ and a time T at which a test of significance is to be conducted. CAT rejects the null at level p if and only if

$$\log C_T(\lambda) > \log(1/p). \quad (12)$$

Under the null hypothesis,

$$Z_T = \frac{\log C_T(\lambda) + (\lambda^2 \sigma^2 / 2)T}{\lambda \sigma \sqrt{T}} \text{ is } N(0,1). \quad (13)$$

Hence CAT rejects the null if and only if

$$Z_T > \frac{\log(1/p) + (\lambda^2 \sigma^2 / 2)T}{\lambda \sigma \sqrt{T}}. \quad (14)$$

To maximize the power of the test we choose the leverage so that the probability of rejection is *maximized*. This occurs when the right-hand side of (14) is *minimized*, that is, when

$$\lambda^* = \frac{\sqrt{2 \log(1/p)}}{\sigma \sqrt{T}}. \quad (15)$$

Notice that λ^* depends on the variance of the process, the time at which the test is conducted, and the level of significance p . However, the corresponding z -value depends only on p , that is, the test rejects if and only if

$$Z_T > \sqrt{2 \log(1/p)} \equiv c_p. \quad (16)$$

We can interpret c_p as the *critical value* of CAT at significance level p . We wish to compare this with the critical value of the t -test, which rejects at level p if and only if

$$Z_T > \Phi^{-1}(1-p) \equiv z_p. \quad (17)$$

Let $L(p)$ denote the *maximum power loss* at significance level p over all combinations of μ, σ, T . In other words, $L(p)$ is the maximum probability that the t -test rejects the null at level p when our test accepts.

Theorem 1. *If CAT is applied to a lognormally distributed asset at significance level p , the maximum power loss $L(p)$ is bounded above by $2\Phi(.5(c_p - z_p)) - 1$. Moreover $L(p) \rightarrow 0$ as $p \rightarrow 0$.*

The proof is given in the Appendix.

Figure 7 plots the upper bound on the power loss $L(p)$ as given in the proposition. Observe that the loss is about 20-25% for p in the range 10^{-3} to 10^{-5} . These p -values are appropriate when we are testing the best asset out of a large population of candidate assets. For example, if we are testing whether the best of 100 assets has positive alpha at significance level 0.01, the asset would have to pass our test at level 0.0001, by the Bonferroni correction.

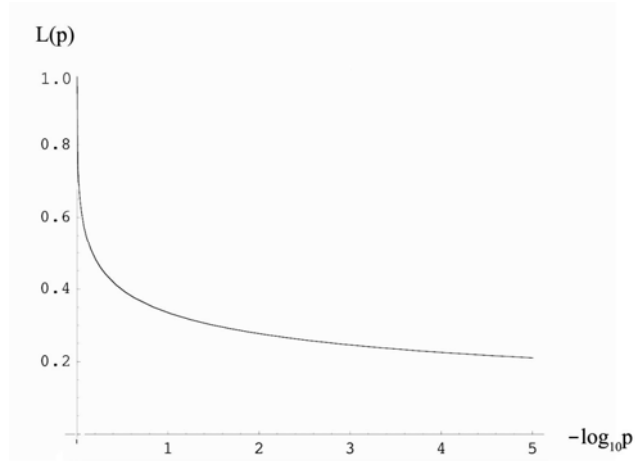


Figure 7. Upper bound on power loss $L(p)$ for *CAT* when the optimal level of leverage is known and the asset can be leveraged in continuous time.

The situation treated in theorem 1 is special in two respects: i) in practice we may not have a precise estimate of the variance, so we cannot use (14) to compute the optimal level of leverage, and ii) in practice we cannot rebalance continuously to maintain a constant level of leverage. Fortunately both of these issues can be dealt with by a suitable modification of our test. The key idea is to choose a range of leverage levels $[0, \bar{\lambda}]$, leverage the asset at each level $\lambda \in [0, \bar{\lambda}]$, and then construct a *hypothetical composite portfolio* that represents a weighted combination of these leveraged assets. We then compute the total return of the portfolio in each period, and apply *CAT* to the final value. We shall call this the *leveraged compound alpha test (LCAT)*.

To be specific, let A_t be the market-adjusted return in period t from the asset we wish to test, as defined in (4). Suppose we wish to leverage the asset by the amount $\lambda > 0$. At the start of period t we invest λ dollars in the asset and $1 - \lambda$

dollars in the risk-free asset (i.e., Treasury bills). Note that if $\lambda > 1$ this means that we are borrowing at the risk-free rate to buy the asset on margin. Given our assumption that we cannot rebalance in continuous time during the course of the period, we need to insure against tail risk by purchasing options. In particular, we need to purchase options that effectively trim off negative realizations of the leveraged returns $1 + \lambda A_t$. This insurance comes at a cost, say $c_t(\lambda, \Delta)$ per dollar of the asset at the start of the period, where Δ is the length of the period. Typically the variance in the returns A_t scales by the factor Δ , and hence for any given value of λ , $c_t(\lambda, \Delta) \rightarrow 0$ as $\Delta \rightarrow 0$. (In the next section we shall analyze a concrete example (Berkshire) in detail, and show that the cost of options insurance is very small when Δ is on the order of one month.)

Let $[0, \bar{\lambda}]$ be a range of leverage levels and let $f(\lambda)$ be a density with full support on $[0, \bar{\lambda}]$. The total return on the λ -leveraged asset in period t is given by the nonnegative random variable

$$B_t(\lambda, \Delta) = \frac{(1 + \lambda A_t)_+}{(1 + c_t(\lambda, \Delta))}. \quad (18)$$

At the start of period $t = 1$, weight the various leverage levels in $[0, \bar{\lambda}]$ according to the distribution $f(\lambda)$. (Note that $f(\lambda)$ determines the initial weighting; the relative amounts invested in the various assets will change over time and are not rebalanced.) The final value of this composite portfolio at the end of period T is

$$C_T(f) = \int_0^{\bar{\lambda}} \prod_{1 \leq t \leq T} B_t(\lambda, \Delta) f(\lambda) d\lambda. \quad (19)$$

The null hypothesis is that $E[A_t] = 0$ for all $t \leq T$, which implies that $E[C_T(f)] \leq 1$. Note that when Δ is sufficiently small, the options costs are small over the entire range $[0, \bar{\lambda}]$, hence the null hypothesis is essentially equivalent to the statement $E[C_T(f)] = 1$. We can therefore reject the null at significance level p if

$$C_T(f) > 1/p. \quad (20)$$

This is the *leveraged compound alpha test (LCAT) with density $f(\lambda)$* . As we have already noted, this test is robust against a wide variety of manipulations that a portfolio manager can employ to make the returns look better than they really are. It is therefore rather surprising to find that the loss in power is actually quite small. In fact, we claim that *LCAT is asymptotically as powerful as the optimal test* when the returns are lognormally distributed and the time periods are short.

Theorem 2. *Consider an asset with market-adjusted returns A_t that are lognormally distributed with unknown mean and variance. Let $f(\lambda)$ be a density with full support on an open interval $(0, \bar{\lambda})$ that contains the optimal level of leverage as defined in (15). Given any small $\varepsilon > 0$, the maximum power loss of LCAT at significance level p , relative to the t -test, is less than ε when p is sufficiently small and the time intervals are sufficiently short.*

This result is related to the pioneering work of Cover (1991) on ‘universal portfolios.’ However, our focus is on estimating the power loss of a particular test relative to the optimal test, which requires a separate proof. The essence of the argument can be sketched as follows (for details see Foster and Young (2011)). We already know from theorem 1 that there exists a level of leverage λ^*

such that *CAT* is asymptotically as powerful as the optimal test for small values of p . In particular, if the t -test rejects the null hypothesis for this leveraged asset, then *CAT* is almost certain to reject it also. This happens if the leveraged asset has grown by a factor exceeding $1/p$. Assets that are leveraged at levels *close* to λ^* will grow by nearly the same factor. Therefore, if the composite portfolio initially puts a positive fraction $q > 0$ of funds into leverage levels near λ^* , the final compound value of the portfolio will grow by a factor of about q/p . (In fact this is an underestimate, because it ignores the growth in value of the assets outside this small neighborhood). In particular, the null will be rejected at the level of significance p/q . It can be shown, however, that the probability of making a type-I error at level p/q is nearly the same as the probability of making a type-I error at level p when p is sufficiently small (and q is fixed). The details are somewhat involved and we shall not give them here; in particular one must show that the argument works when the costs of options are taken into account (see Foster and Young, 2011).⁷

5. Empirical analysis

In this section we shall apply our framework to the three assets shown in Figures 1-4, with a particular focus on Berkshire. Let us recapitulate the basic steps in the test. We are given a candidate asset whose returns are observed over T periods: Y_1, Y_2, \dots, Y_T . Denote the market returns over the same T periods by M_1, M_2, \dots, M_T , where the “market” refers to some broad-based index such as the S&P 500 or the

⁷ Foster and Young (2011) use the martingale maximal inequality as a test of excess returns. This is a more powerful test than the Markov inequality when applied to martingale data. However, their estimates of power loss are based on the Markov inequality applied to end-of-period value (just as we do here), hence their estimates are valid in the present situation.

Wilshire 5000. Denote the risk-free rates of return by r_1, r_2, \dots, r_T .

Step 1. Compute the regression coefficient β between the asset's excess returns $\tilde{Y}_t = Y_t - r_t$ and the market's returns excess returns $\tilde{M}_t = M_t - r_t$:

$$\beta = \frac{\sum_{1 \leq t \leq T} (\tilde{Y}_t - \bar{\tilde{Y}})(\tilde{M}_t - \bar{\tilde{M}})}{\sum_{1 \leq t \leq T} (\tilde{M}_t - \bar{\tilde{M}})^2}.$$

Step 2. For each t compute the *market-adjusted return*

$$A_t = \tilde{Y}_t - \beta \tilde{M}_t$$

Step 3. Choose a range of leverage levels $0 < \lambda_1 < \lambda_2 < \dots < \lambda_m$. Estimate the cost $c_t(\lambda_k)$ of insuring the λ_k -leveraged asset against default during period t . For each t and each value λ_k compute the *insured returns*

$$B_{t,k} = [1 + \lambda_k A_t]_+ / (1 + c_t(\lambda_k)).$$

Step 4. Compute the compound values

$$C_k = \prod_{1 \leq t \leq T} B_{k,t} \quad \text{and} \quad \bar{C} = (1/m) \sum_{1 \leq k \leq m} C_k.$$

Step 5. Reject the null hypothesis at level p if $\bar{C} > 1/p$.

How should one choose the range of leverage levels in step 3? One approach is the following. The expected long-run growth rate of any asset is roughly equal to its mean return minus one-half of the variance (the volatility drag). (In fact this statement holds exactly if the returns are lognormally distributed.) This suggests that to maximize the compound value of the leveraged market-adjusted returns, one should choose the leverage equal to the mean divided by the variance of the returns. Since this is only a rough estimate of the optimal leverage level, we should in fact choose a range of levels on either side of the estimate.

We shall now illustrate this procedure by analyzing the performance of Berkshire Hathaway from November 1976 to December 2010.⁸ The overall beta for the period is $\beta = .67$. The mean market-adjusted return $\bar{A} = E[A_t]$ is 0.0127 per month and the variance is 0.000427 per month. Thus we take $\lambda = 0.0127 / 0.000427 \approx 3$ as a reasonable place to center the range of leverage levels.

Next we compute the compound value of the market-adjusted leveraged returns at each of the levels $\lambda = 1, 2, 3, 4, 5$ but without including options costs. The growth in these compound values over the period is shown in Figure 8. The maximal final value in 2010 was 4,426 (leverage 3). When the five levels are weighted equally the final value is $\bar{C} = 1,834$.

⁸ A similar analysis can be applied to Team but it turns out that leveraging does little to increase the compound returns over the observation period. The analysis cannot be applied to the Piggyback Fund because there is no way to insure the returns, hence the fund cannot be leveraged.

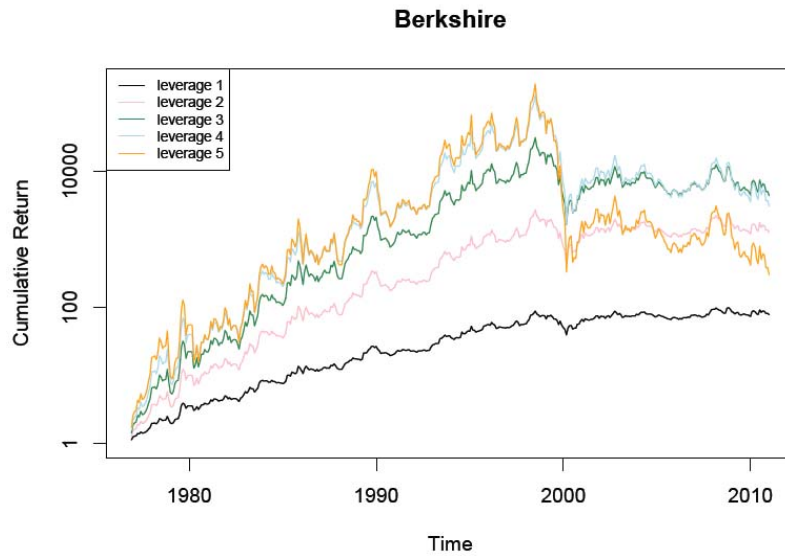


Figure 8. Compound value of market-adjusted returns on Berkshire Hathaway, leveraged at five different levels over the period Nov 1976 - Dec 2010.

The reciprocal of the value \bar{C} gives us a preliminary estimate of the level of significance (in this case $1/\bar{C} = 0.00054$). If the result is not significant we need proceed no further. If it is significant, however, we need to refine the analysis by including the cost of insuring that the returns stay non-negative. For example, to protect the market-adjusted return $A_t = \tilde{Y}_t - .67\tilde{M}_t$ for one month leveraged five times, one could buy five puts on Berkshire and five calls on the market that expire in 30 days. The strike prices need to be chosen to protect against a decline of more than 20% in the value of A_t . This will be true if the puts protect against a fall of more than x% in Berkshire and the calls protect against a rise of more than y% in the market, where $x + .67y = 20$. The least costly combination depends on the relative volatility of Berkshire versus the market, where the latter is taken to be the S & P 500.

Using data on options prices in May 2011, we estimated the cost of insuring Berkshire at five different amounts of leverage, as shown in columns 1 and 2 of Table 2.

Leverage	Reduction in Monthly Return	Final Value of BRK		p-value
		Without Option	With Option	
1	nil	\$ 79	\$ 79	0.0130
2	0.00040	1265	1073	0.00093
3	0.00118	4426	2722	0.00037
4	0.00198	3095	1379	0.00072
5	0.00542	305	33	0.030
Average	0.00112	1834	1057	0.00095

Table 2. Results for leveraging Berkshire and accounting for option costs.

The cost of insurance reduces the final compound value as shown in columns 3 and 4. Column 5 shows the level of significance corresponding to the final compound value net of options costs. It turns out that three times leverage generates the highest final compound value (2,722). The average value over the five leverage levels is $\bar{C} = 1057$, which corresponds to a p -value of 0.00095. Note that the inclusion of options costs does not change the level of significance by very much: when options costs are not included the final average value is 1,834, which corresponds to the p -value 0.00055.

Although these p -values would be highly significant when viewed in isolation, we need to correct for multiplicity using Bonferroni. In particular, Berkshire was

picked from the S&P 500 precisely because of its outstanding long-run performance. Adjusted for multiplicity, its p-value is $0.00095 \times 500 = 0.475$, which is not significant. In other words, out of 500 stocks there is nearly a 50% chance that at least one of them will do as well as Berkshire.

Appendix: Proof of Theorem 1

Let $c_p = \sqrt{2\ln(1/p)}$ and let z_p be the z-value corresponding to the level of significance p . We need to show that

$$L(p) < 2\Phi(.5(c_p - z_p)) - 1 \text{ and } \lim_{p \rightarrow 0^+} L(p) = 0. \quad (\text{A1})$$

Under the null hypothesis ($\mu = 0$),

$$Z_t = \frac{\ln C_t + .5(\lambda * \sigma)^2 t}{\lambda * \sigma \sqrt{t}} = \frac{\ln C_t + .5c_p^2}{c_p} \text{ is } N(0,1). \quad (\text{A2})$$

Hence the t -test rejects the null at level p if and only if

$$z_p < \frac{\ln C_t}{c_p} + .5c_p. \quad (\text{A3})$$

By contrast, CAT accepts the null if and only if $\ln C_t \leq \ln(1/p) = .5c_p^2$, that is,

$$\frac{\ln C_t}{c_p} \leq .5c_p. \quad (\text{A4})$$

Power loss occurs in the region where both (A3) and (A4) hold.

Assume now that $\frac{\ln C_t}{c_p} + .5c_p$ is distributed $N(\frac{\mu\sqrt{t}}{\sigma}, 1)$ for some $\mu > 0$. For this μ, σ , and t the loss in power is the probability of the event

$$z_p - \frac{\mu\sqrt{t}}{\sigma} < \frac{\ln C_t}{c_p} + .5c_p - \frac{\mu\sqrt{t}}{\sigma} \leq c_p - \frac{\mu\sqrt{t}}{\sigma}. \quad (\text{A5})$$

The middle term is distributed $N(0, 1)$, so the probability of this event is

$$\Phi(c_p - \frac{\mu\sqrt{t}}{\sigma}) - \Phi(z_p - \frac{\mu\sqrt{t}}{\sigma}). \quad (\text{A6})$$

This probability is maximized when $z_p - \frac{\mu\sqrt{t}}{\sigma}$ and $c_p - \frac{\mu\sqrt{t}}{\sigma}$ are symmetrically situated about zero. It follows that the maximal power loss function satisfies

$$L(p) \leq 2\Phi(.5(c_p - z_p)) - 1. \quad (\text{A7})$$

To complete the proof, we need to show that $c_p - z_p \rightarrow 0^+$ as $p \rightarrow 0^+$. Recall that when z is large the right tail of the normal distribution has the following approximation [Feller, 1971, p.193]:

$$P(Z \geq z) \approx \frac{e^{-z^2/2}}{z\sqrt{2\pi}}. \quad (\text{A8})$$

By definition $P(Z \geq z_p) = p$. From this and (A8) we conclude that

$$z_p^2 \approx c_p^2 - 2 \ln \sqrt{2\pi} - 2 \ln z_p . \quad (\text{A9})$$

Hence

$$c_p - z_p \approx 2(\ln \sqrt{2\pi} + \ln z_p) / (c_p + z_p), \quad (\text{A10})$$

which implies that $c_p - z_p \rightarrow 0^+$ as $p \rightarrow 0^+$. This concludes the proof of the theorem.

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