Head and Shoulders above the Rest? The Performance of Institutional Portfolio Managers who Use Technical Analysis

David Smith

Christophe Faugère

and

Ying Wang

January 2013

Department of Finance and Center for Institutional Investment Management, School of Business, University at Albany (SUNY), Albany, NY 12222 USA. C. Faugère is also affiliated with KEDGE/BEM Bordeaux School of Management, France.

Head and Shoulders above the Rest? The Performance of Institutional Portfolio Managers who Use Technical Analysis

Abstract

This study takes a novel approach to testing the efficacy of technical analysis. Rather than testing specific trading rules as is typically done in the literature, we rely on institutional portfolio managers' statements about whether and how intensely they use technical analysis, irrespective of the form in which they implement it. In our sample of more than 10,000 portfolios, about one-third of actively managed equity and balanced funds use technical analysis. We compare the investment performance of funds that use technical analysis versus those that do not using five metrics. Mean and median (3 and 4-factor) alpha values are generally slightly higher for a cross section of funds using technical analysis, but performance volatility is also higher. Benchmark-adjusted returns are also higher, particularly when market prices are declining. The most remarkable finding is that portfolios with greater reliance on technical analysis have elevated skewness and kurtosis levels relative to portfolios that do not use technical analysis. Funds using technical analysis appear to have provided a meaningful advantage to their investors, albeit in an unexpected way.

Keywords: Technical analysis, portfolio management, institutional investment

JEL: G11, G12, G23

For decades the academic profession has derided and essentially relegated technical analysis to the same status as alchemy (Malkiel, 2003). Yet technical analysis remains a staple among many retail and institutional investors. Park and Irwin (2007) report that 30-40% of surveyed foreign exchange traders believe that technical analysis is an important tool for determining price movement at shorter time horizons up to 6 months.

Past studies have tended to show that technical analysis does not outperform simple buy-and-hold strategies after transaction costs are accounted for (Fama and Blume, 1966). However, many recent studies do find evidence in favor of technical analysis, including Brock, Lakonishok, and LeBaron (1992), Blume, Easley, and O'Hara (1994), Chan, Jegadeesh, and Lakonishok (1996, 1999) and Lo, Mamaysky, and Wang (2000). For example, Brock, Lakonishok, and LeBaron (1992) analyze two of the most popular indicators of technical analysis: the moving average and the trading range break-out strategy. They show that greater returns follow buy-signals in contrast to sell-signals. Returns after buy-signals are less volatile than after sell-signals.

The standard approach in the literature is to recreate known technical trading rules and analyze their results in various markets. This approach has several shortcomings. First, the trading strategies tested in the literature are relatively unsophisticated and do not account for the dynamic and flexible aspect of actual technical trading strategies. For example, *combinations* of rules are usually not tested. Second, no amount of evidence rejecting the value of tested technical trading rules can prove that some *untested* ones used by practitioners do not outperform buy-and-hold investment strategies. Third, tests of these strategies fall victim to the infamous data snooping bias (Lo and MacKinlay, 1990; Brock, Lakonishok, and LeBaron, 1992). Some strategies may appear to be winners purely by luck, because they are retrofitted to the actual observed history, rather than based on the distributional properties of market returns and out-of sample data. White's Reality Check (White, 2000) is a popular methodology developed to remedy this issue, but it is not a panacea, especially given that it is based on a universe of "tested" rules that by construction does not include all actual rules. For example, Sullivan, Timmermann, and White (1999) test 7,846 trading rules, drawn from five commonly used classes of rules in financial markets. Although 7,846 is a large number, this collection may not be comprehensive enough. Several well-known classes of trading rules, such as momentum strategies, are not included in the study. Of course, later studies have augmented the size of the trading rules universe (Hsu and Kuan, 2005), but the same fundamental issue persists.

Essentially, academic studies have not been able to peer into and reproduce the content of the black box of tools used by professional chartists. In this article, we tackle the issue from a different angle. While we do not attempt to find out what is in the black box, we use information obtained directly from portfolio managers about their use of technical analysis as a primary investment tool and analyze the performance of their funds.

LITERATURE REVIEW

Bachelier (1900) was the first author to show that stock prices followed a random walk. It was later in the 1950s and 1960s that this statistical property was rediscovered for example in the work of Alexander (1961), and later cast as the Efficient Market Hypothesis. Fama (1965a) originated the concept of an “efficient” market. Harry Roberts (Roberts, 1967) coined the term Efficient Markets Hypothesis and made the distinction between weak and strong form tests, which became the classic taxonomy in Fama (1970). However, Samuelson (1965) was the first to give a rigorous formulation of the Efficient Market Hypothesis (EMH): the market is efficient and prices are equal to fundamental values when there is perfect competition, assuming all participants have free access to all relevant information. In that case, all the relevant information is incorporated into prices, and prices follow a martingale process. Hence, no one should expect to profit from statistical or chart analysis of past prices. Fama (1965b) added a touch of delectable irony in stating that the theory of random walks in stock market prices constitutes an important challenge to the proponents of both technical analysis and fundamental analysis.

Despite having received these almost lethal blows from these foundational concepts of finance, technical analysis could still be rescued on the grounds that some of the underlying assumptions in the rational expectations model of Samuelson (1965) are incorrect. One example is assumptions about how investors process information. *Noisy* rational expectations models offer an alternative view in which the current price does *not* fully reveal all available information because of noise, useless chatter with no informational content. Because of noise, stock prices may adjust slowly to new information and this may lead to profitable trading opportunities.

Working (1958) was the first to develop a model in which traders are divided into two groups: a large group of well- informed traders and a small group of ill- informed traders.

In his model, prices tend to change gradually and frequently. The tendency of gradual price changes produces short-term predictability.

Grossman and Stiglitz (1976, 1980) developed a formal noisy rational expectations model. Their model also assumes two types of traders, “informed” and “uninformed,” depending on whether they paid a cost to obtain information. In the end, their model supports only the weak form of the EMH in which no profits are made from using price history because uninformed traders have rational expectations.

Another lifeline was thrown to technical analysis by the 1990s literature that focused on behavioral explanations of market prices. Assume there are two types of investors: arbitrageurs and noise traders. Arbitrageurs are investors who have fully rational expectations about security returns, while noise traders are investors who irrationally trade on noise *as if* it were information (Black 1986). Noise traders’ demand for stocks is somewhat disconnected from news or fundamental factors (Shleifer & Summers, 1990). In these models, noise traders are momentum traders. They buy when prices rise and sell when prices fall. Arbitrageurs anticipate that price movements away from fundamentals are possible, and hence may even contribute to amplify these movements, when trying to capture these momentum gains. These models suggest that technical trading profits may be available when a category of investor trades based on noise and not on information such as news or fundamental factors.

Empirically, most of the documented use of technical analysis by traders has been gathered from commodity futures and currency markets. In one of the earliest survey studies on technical analysis, Stewart (1949) analyzed the trading behavior of customers of a large Chicago futures commission firm from 1924 to 1932. He found that these grain futures trading strategies were generally unsuccessful. Brorsen and Irwin (1987) surveyed large public futures funds' advisory groups in 1986. Over 50% of them relied heavily on algorithmic trading systems. Taylor and Allen (1992) conducted a survey among foreign exchange dealers on the London market in 1988. Sixty-four percent of respondents reported using trend-following systems and 40% reported using other trading techniques such as momentum indicators. Furthermore, approximately 90% of respondents reported that they were using some technical analysis when forming their exchange rate expectations at the shortest horizons (intraday to one week), with 60% viewing technical analysis to be at least as important as fundamental analysis.

Lui and Mole (1998) surveyed the use of technical and fundamental analysis by foreign exchange dealers in Hong Kong in 1995. These dealers stated that technical analysis was more useful than fundamental analysis in forecasting both trends and turning points. Cheung and Chinn (2001) surveyed US-based foreign exchange traders in 1998. About 30% of the traders indicated that technical trading best describes their trading strategy.

Fama and Blume (1966) is the best-known and most influential early work on testing technical trading rules. The authors exhaustively tested Alexander's (1961, 1964) filter rules on daily closing prices of the 30 Dow Jones Industrial Average securities during the 1956-1962 period. Their results showed that filter rules were inferior to a simple buy-and-hold strategy for all but two securities.

Overall, in the early studies from the 1960s and 70s, very limited evidence of the profitability of technical trading rules was found *in stock markets* (Fama and Blume 1966; Van Horne and Parker 1967; Jensen and Benington 1970), while technical trading rules often realized sizable net profits in futures markets (Stevenson and Bear 1970; Irwin and Uhrig 1984) and foreign exchange markets (Poole 1967; Cornell and Dietrich 1978; Sweeney 1986). Thus, the stock market appeared to be *efficient* relative to futures markets or foreign exchange markets during the time periods examined.

Among modern studies, one of the most influential works on technical trading rules is that of Brock, Lakonishok, and LeBaron (1992) (BLL). BLL recognized the danger of data snooping biases in technical trading studies. Their paper features the use of a very long price history and, for the first time, model-based bootstrap methods for making statistical inferences about technical trading profits. The bootstrap procedure compares returns conditional on buy (or sell) signals from the original series to conditional returns from simulated series generated by widely used models for stock prices. BLL tested two simple technical trading systems, a moving-average oscillator and a trading-range breakout (resistance and support levels), on the Dow Jones Industrial Average (DJIA) from 1897 through 1986. They showed that greater returns follow buy-signals in contrast to sell-signals. Returns after buy-signals are less volatile than after sell-signals.

Still their study may have suffered from several shortcomings. For example, Bessembinder and Chan (1998) conclude that, although the technical trading rules used by BLL revealed some forecasting ability, it was unlikely that traders could have used the trading rules to improve returns net of transaction costs.

Ready (2002) compared the performance of technical trading rules developed by genetic programming to that of moving-average rules examined by BLL for dividend-adjusted DJIA data. BLL's best trading rule for the 1963-1986 period generated substantially higher excess returns than the average of trading rules formed by genetic programming after transaction costs. For the 1957-1962 period, however, the same rule underperformed every one of genetic trading rules. Thus, it seemed unlikely that this rule would have been chosen by a hypothetical trader at the end of 1962.

In the literature on technical trading strategies, a fairly blatant form of data snooping is an ex post and "in-sample" search for profitable trading rules. White's (2000) seminal paper develops a statistical procedure that can assess the effects of data snooping in the traditional framework of pre-determined trading rules. The so-called Bootstrap Reality Check methodology tests a null hypothesis that the best trading rule performs no better than a benchmark strategy. In this approach, the best rule is searched by applying a performance measure to the full set of trading rules, and a desired p-value can be obtained from comparing the performance of the best trading rule to approximations to the asymptotic distribution of the performance measure.

Sullivan, Timmermann, and White (1999) applied White's Bootstrap Reality Check methodology to the DJIA, from 1897 through 1996. They used the same sample period (1897-1986) studied by BLL (1992) for in-sample tests and an additional 10 years from 1987-1996 for out-of-sample tests. Sullivan, Timmermann, and White considered 7,846 trading rules, drawn from five commonly used classes of rules in financial markets that consisted of filters, moving averages, support and resistance, channel breakouts, and on-balance volume averages. Overall, Sullivan, Timmermann, and White found that poor out-of-sample performance relative to the significant in-sample performance for the DJIA. They conclude that this poor performance might be related to the recent improvement of the market efficiency due to the cheaper computing power, lower transaction costs, and increased liquidity in the stock market.

HYPOTHESES

In this paper; we examine a single overarching hypothesis that can be stated as follows:

H_1: Technical Analysis confers a risk-adjusted performance advantage to funds which use it more intensely.

In the hypothesis above, technical analysis is understood to be the set of trading rules applied by fund managers even though they are unobserved. As noted in the literature review, technical analysis continues to enjoy substantial popularity in the practitioner world where cost/benefit analysis underlies many policies. It is unlikely that investment companies would persist in funding employees with a technical analysis orientation and related skills if the value added were considered insufficient. Our contention is that any finding that a particular technical analysis method outperformed is unlikely, given that few portfolio managers are willing to reveal their specific alpha-generating strategies. Moreover, even if specific strategies were tested and found to be unprofitable, technical analysts can make the credible claim that they apply the strategy slightly differently, and that in this nuance lies the profit source. Testing the value of technical analysis more holistically – without regard to specific method – is likely to be more fruitful.

DATA AND EMPIRICAL TESTS

Data for this study are drawn from the PSN Enterprise ("PSN") database, a product of Informa Investment Solutions. PSN is commonly used by investment consultants and their clients. The database contains descriptive and performance information on more than 14,000 professionally managed institutional portfolios under the control of over 2,000 investment firms. Variables available include manager name and educational and professional credentials, portfolio size and sector composition, name of the primary performance benchmark, and monthly returns. PSN is survivor-bias free.

What makes the database uniquely useful for the present study is that PSN also surveys portfolio managers about the main elements of their current decision process. Twenty-four distinct equity decision-making fields are presented, and managers are asked to rate the importance s/he places on each one. For example, one of the 24 questions asks about the relative importance of technical analysis in managing the portfolio. Possible responses include that in managing the portfolio, technical analysis is "very important," "important," "utilized," "not important," or "not utilized." Managers are permitted to respond in one of those five ways and establish a usage ranking for any or all of the 24 criteria. Despite the flexibility to choose "very important" for all criteria, most portfolio managers limit that rating to very few choices.

An additional question in the survey asks managers to indicate the single criterion that is their *primary* equity decision criterion. Any of the 24 criteria referenced earlier – including technical analysis – can be designated the primary decision criterion. As documented by Shawky and Smith (2012), by far the most commonly used criteria across the universe of equity managers are various forms of fundamental analysis and various forms of quantitative/computer screening. They find that technical analysis is well down the list, with fewer than ½ of 1% of all professional equity portfolio managers using that method as their primary decision criterion. Notwithstanding those observations, the data used in the present study show that technical analysis remains alive and well as a companion to other equity decision strategies.

This paper's sample is derived from the PSN database as of July 2012. PSN covers 14,973 professionally managed institutional portfolios, 7,295 of which are currently active. We screen out non-equity funds, index funds and semi-actively managed funds, and funds whose managers declined to respond to the PSN survey question about technical analysis. This leaves an initial sample of 10,452 actively managed U.S. equity, international/global equity, U.S. balanced, and international/global balanced portfolios. Balanced funds are permitted to invest in both equity and fixed-income securities

Table 1 about here

Table 1 reports the response frequency to the question of how important or utilized technical analysis is among equity portfolio managers. Depending on the investment type, technical analysis is cited as very important, important, or utilized by between 13-32% of respondents. It is most commonly employed by U.S. equity managers and least by U.S. balanced-fund managers. It has been said that while fundamental analysis helps stock pickers determine *what* to buy and sell, technical analysis helps answer the question of *when* to buy and sell. Over 85% of U.S. balanced fund managers respond that technical analysis is not used or not important. This is somewhat surprising given that balanced-fund managers must make asset allocation decisions that often depend on the relative valuations of these asset classes. On the other hand, almost one-third of international/global balanced funds in Table 1 find technical analysis to be useful and even important. While beyond the scope of this study, this raises the question of whether technical analysis helps to make timing decisions when institutional investors choose among various global markets.

Table 2 reports the responses of U.S. equity fund managers, listed according to the market capitalization of their portfolio holdings. The use of technical analysis does not vary greatly by market cap of holdings. About two-thirds of investors who focus on a capitalization sector consider technical analysis to be useful or important. Another notable point in Table 2 is that a relatively high 5.9% of All-Cap funds consider technical analysis to be very important.

Table 2 about here

Table 3 provides evidence about the degree to which portfolio managers using technical analysis also employ 19 other types of equity decision-making criteria. The table contains correlation coefficients between technical analysis responses (ranging from 1-5, from not utilized to very important) and the responses for each of the other criteria listed.

By far the highest correlation is for momentum. This is consistent with technical analysis being strongly related to price and volume trends, and this high correlation serves as an important reliability check on the data. Another cluster of decision criteria relates to industry-sector analysis, investing based on themes (including deflation, energy shortages, changing consumption patterns, and other themes), and quantitative/computer screening. Interestingly, one of the two primary forms of fundamental analysis, top-down analysis, is found in the second cluster with correlations around 0.25. For managers answering “fundamental analysis” and its other principal form, “bottom-up,” the correlations are quite low at 0.107 and 0.035, respectively.

Table 3 about here

Table 4 provides additional granularity for the nine most common primary equity decision making criteria. Again, respondents in the PSN survey can choose only *one* primary decision criterion, and bottom-up stock picking is the most common method by more than a factor of four over the second-place criterion. For the more than 4,000 portfolios managed using fundamental analysis or bottom-up stock picking, about two-thirds consider technical analysis to be unimportant at best.

Managers using certain other decision criteria have bi-modal opinions about the value of technical analysis. These differences are manifested in nearly uniform relative frequencies. Consider top-down/economic analysis, for which 30% of portfolios utilize technical analysis and 32% do not. Similarly, theme identification has nearly equal values of users and non-users of technical analysis at about 36%. Clearly, some decision criteria are amenable to being pursued with or without technical analysis as a complement. Portfolio managers employing other methods, such as quantitative/computer screening and also criteria associated with bottom-up stock pricing, are more unanimous in asserting that technical analysis is not complementary to their styles.

Table 4 about here

Some adherents of technical analysis argue that special skills are required. The Chartered Market Technician (CMT) program provides a formalized curriculum and whose successful completion requires three exams plus significant work experience. It is offered by the Market Technicians Association. PSN provides information about the extent to which portfolios managed using technical analysis employ specialists holding the CMT designation. Five percent of portfolios for which managers said technical analysis is “very important” are at least co-managed by someone who holds the CMT designation. Two percent of those rating technical analysis “important” have a CMT holder on staff, and one percent of those answering “utilized,” “not important,” or “not utilized” employ someone who has earned a CMT.

RESULTS

This section contains a comparison of the portfolio performance of institutional investment managers who use technical analysis versus those who do not or who consider it unimportant. The aim is to confirm whether portfolio managers' responses are compatible with investor wealth maximization.

We measure performance in multiple ways. Investors who have a goal of earning absolute returns often focus on raw rate of return (ROR) to the exclusion of most other measures. Yet even unsophisticated investors realize that a portfolio's main goal is to beat a benchmark index's performance. Consequently, performance measures net out the return of a benchmark index. PSN identifies each portfolio's primary performance benchmark, and also reports each benchmark's monthly returns. This facilitates calculation of monthly average returns net of the benchmark (benchmark-adjusted return, which we abbreviate BAR) and also the standard deviation of that measure.

The mean BAR divided by the standard deviation is the information ratio, originally proposed by Treynor and Black (1973). The information ratio indicates the return gained by deviating from the benchmark, scaled by the extent of that deviation over time. Although portfolio-versus-benchmark comparisons are key performance measures, they do not adjust fully for known market risk factors. Fama and French (1993) and Carhart (1997) propose, respectively, three- and four-factor models to evaluate managers' ability to generate excess return, or alpha. Fama and French use the market risk premium of the Capital Asset Pricing Model, a size premium to capture small-cap stocks' higher risk than large-cap stocks, and a book-to-market premium to reflect the higher riskiness of value stocks than growth stocks. Their model takes the following form:

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{m,t} - R_f) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \epsilon_{i,t} , \tag{1}$$

where $R_{i,t}$ is the return of portfolio *i* in month *t*, R_f is the risk-free rate, $R_{m,t}$ is the market return, and SMB_t and HML_t are the month-*t* returns on factor-mimicking portfolios for size and book-to-market equity, respectively. Carhart (1997) adds a fourth factor that reflects a momentum premium, incorporating high-momentum stocks' outperformance relative to low-momentum stocks, as follows:

$$R_{i,t} - R_f = \alpha_i + \beta_{i,m}(R_{m,t} - R_f) + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,UMD}UMD_t + \epsilon_{i,t} \text{ ,(2)}$$

where UMD_t is the month-*t* returns on factor-mimicking portfolios for one-year momentum in stock returns. We include a portfolio in a month's performance calculation only if the current manager was employed at the fund during that month. All months of returns prior to the present manager's service are deleted, because we assume that only the present manager's survey results concerning technical analysis are valid and relatable to portfolio performance. The previous manager may well have had a different policy about the use of technical analysis, and the fund's performance may have differed accordingly.

Table 5 about here

Table 5 presents results for several of the aforementioned performance measures. In each case the numbers are shown according to managers' usage of technical analysis. For

ROR and BAR, we calculate equally weighted portfolio returns for each ranking category for each month, and then calculate the time-series summary statistics shown in the table over the 231 months between January 1993 and March 2012. For inclusion, we require a portfolio to report at least 30 months of returns.

The performance measures' higher moments suggest an assumption of non-normality is appropriate, leading to concerns that standard parametric tests may be biased. However, the sample sizes are large and the observations independent, so the Central-Limit Theorem can be invoked. Consequently, we report standard analysis of variance (ANOVA) tests of means alongside nonparametric tests that evaluate differences in medians.

Both ANOVA and Kruskal-Wallis tests indicate that the performance measures' means and medians are statistically different from their counterparts across technical analysis usage rankings. This is strong evidence that central tendency measures of ROR and BAR are dependent on technical analysis usage categories. Moreover, a homogeneity-of-variances test between the "Very Important" group and a combination of the "Not Important" and "Not Utilized" groups shows that former is significantly larger.

Based another performance measure, the information ratio, one might conclude that funds using technical analysis underperform those that do not. The BAR advantage of technical-analysis portfolios is offset by an even higher standard deviation of BAR, causing a lower information ratio. Without considering higher moments, this could be interpreted to mean that active management is relatively ineffective in portfolios managed using technical analysis.

However, Table 5 is the first of several that will show the importance of considering higher moments. First, the skewness of performance measures generally tends to be higher for portfolios that use technical analysis. Investors have long considered negative skewness to be an aversive attribute as shown by Arditti (1967) and Kraus and Litzenberger (1976). Levy and Sarnat (1984) link this positive skewness preference to investors' willingness to accept a lower rate of return.

Investors' kurtosis preferences are somewhat more ambiguous and even dependent on the characteristics of the lower distributional moments. Damodaran (2002) and Haas (2007) suggest that the more frequent "jumps" associated with a leptokurtotic distribution may produce a higher required return. A similar concept is co-kurtosis, which relates kurtosis to skewness. As noted by Guidolin and Timmermann (2008), a high portfolio co-kurtosis value increases the chance that in a right-skewed market the portfolio return will be high, while it will be low when the market is left-skewed.

Table 6 about here

Table 6 provides summary statistics for the 3-factor and 4-factor alphas. Once again, ANOVA and Kruskal-Wallis tests confirm that the mean and median alphas are statistically different across technical analysis usage rankings. Variances for the two groups as described in Table 5 are also significantly different from one another. Particularly striking in Table 6 are the extremely high skewness and kurtosis figures for funds whose managers consider technical analysis to be "very important." Indeed, these sample statistics are almost monotonically related to the technical analysis usage rating.

Table 7 about here

The analysis next turns to specific market conditions that technical analysis strategies may be designed to detect or even forecast. Table 7 reports the results from January 1993 to March 2012 of portfolio returns net of benchmark under differing market conditions. The first condition is a positive contemporaneous month's market return, and the second condition is a negative contemporaneous market return. We operationalize this by measuring portfolio performance and calculating sample statistics only in months when returns are positive or negative, respectively. Given that technical analysis purports to give traders an edge in market timing, it is expected that performance metrics during down months in particular will be superior for portfolios using technical strategies. The third and fourth market conditions have a similar motivation. The third measures the portfolio's performance only in the months for which market return is of the same sign as the return in the previous month ("continuations"). The fourth is for only months in which the previous month's return is reversed ("reversals").

With respect to means, medians, standard deviations, and kurtoses of ROR, in Table 7 no clear pattern emerges between technical analysis users and non-users. Consistent with results shown in previous tables, return skewness is consistently higher for technical analysis portfolios than for their counterparts.

Table 8 about here

Table 8 contains performance results for BARs under the same conditions as were discussed for Table 7. It is particularly interesting to note the relations for positive and negative market environments. In Table 7, the means and medians of portfolio ROR moved decisively in the same direction as the overall equity market. Table 8 nets out the primary performance benchmark's return for each portfolio. A comparison of the results in Panels A and B reveals that managers are much better able to beat their benchmarks when the market *declines* than when it is rising. When the benchmark return is positive, portfolio managers find it comparatively difficult to keep pace. One possible reason for the enhanced outperformance in negative months is that managers can increase cash holdings and thus buoy net returns. Even so, both the technical analysis user and nonuser beat the market index. Panel B of Table 8 contains the lone statistically significant result for average performance. On the basis of BAR, managers who consider technical analysis to be very important outperform those who do not use it by an average of *19 basis points per month*, which is different from zero at the 5% significance level. Although this result is not confirmed by a nonparametric difference-of-medians test, there is directional consistency. Thus, the data provide some evidence that technical analysis conveys an advantage when market prices decline.

Figure 1 about here

Figure 1 shows the cumulative value of $1 invested on January 1, 1993 in portfolios managed using technical analysis versus those that are not. The former portfolios have maintained a status of outperformance since the end of the first decade.

Given the general finding of a higher performance standard deviation for portfolios associated with technical analysis, a question arises about whether the managers take on risk to a level that produces a higher failure risk for the fund. This is not easy to test directly because PSN does not provide a time series of its survey results, so as to link a past usage of technical analysis to subsequent performance. We have only the most recent response from each portfolio's manager concerning technical analysis, plus historical returns. What PSN supplies is a record of whether a portfolio is active in its database or inactive. In our sample, 55% of portfolios for which managers state that technical analysis is not utilized have survived to the present. Portfolios associated with the other four possible responses have survived at a 45-48% rate, with the "technical analysis is very important" category at the top of that range.

Robustness

The greatly unbalanced sample sizes for funds in the "very important" versus "not important/not utilized" groups may produce questionable inferences from any tests, particularly insofar as the sample variances are unequal. In an effort to balance the sample sizes we create a matching sample for the former funds with counterparts from the other groups. The bases for matching are threefold. The matching fund must 1) be in the same asset class, e.g., U.S. domestic equity or global balanced; 2) focus on the same market capitalization, e.g., all-cap, or large-cap, and 3) have the same primary equity investment style, e.g., value, growth, or core diversified. A total of 238 funds met the matching criteria. Although performance measures are not available for all of these funds, the sample sizes are much more similar. The untabulated results for the "matched" sample are qualitatively similar to those shown for the whole sample, which increases confidence in our previously reported results.

With the exception of Tables 2 and 4, the sample for this paper includes consolidated U.S. equity, international/global equity, U.S. balanced, and international/global balanced portfolios. We confirm that the analysis conducted using only U.S. domestic equity portfolios leaves all the reported results qualitatively unchanged.

CONCLUSIONS

Past work focuses on testing the full array of specific technical analysis strategies and this carries several problems. One shortcoming is that such testing involves chasing a moving target, because the number of potential strategies is infinite. Researchers' conclusions that a specific strategy fails to work raises the question of whether portfolio managers actually succeed by implementing a slight variation. Moreover, any portfolio manager who finds that a technical-analysis strategy produces outperformance has little incentive to reveal that method to researchers. Thus, strategies that do work are likely to remain concealed.

This examination of technical analysis brings a different approach. Rather than testing specific strategies, we rely on institutional portfolio managers' assertions about the extent to which they use technical analysis, irrespective of the form in which it is implemented. We use survey responses collected by Informa Investment Solutions and that populate the PSN Enterprise database.

We find that technical analysis is utilized by only about one-third of U.S. and international/global equity and balanced portfolio investors. International/global balanced fund managers use it the most, and U.S. balanced the least. Among equity fund managers, it is slightly more common for micro-cap and all-cap managers.

How effective is technical analysis? To answer this question we examine five performance metrics: raw rate of return, benchmark-adjusted return, information ratio, 3-factor alpha, and 4-factor alpha. With respect to mean and median values, the performance advantage of technical analysis is slight, but statistically significant. The contrast appears more salient during down markets, and when performance is measured relative to a primary benchmark. Also, variability is somewhat increased in technically managed portfolios. However, the cross-section of portfolios managed using technical analysis shows remarkably elevated skewness and kurtosis values relative to portfolios that do not use technical analysis. In the presence of the former, the latter can be advantageous. In view of these results, we conclude that the net effect of technical analysis on the management of institutional equity-related portfolios has been beneficial, although in an unexpected way.

REFERENCES

Alexander, S. S. (1961). Price movements in speculative markets: Trends or random walks. *Industrial Management Review* 2, 7–26.

Alexander, S. S. (1964). Price movements in speculative markets: Trends or random walks No. 2." *Industrial Management Review* 5, 25-46.

Arditti, F. D. (1967). Risk and the required return on equity. *The Journal of Finance* 22, 19-36.

Bachelier, L. (1900). Théorie de la spéculation. *Annales Scientifiques de l'Ecole Normale Supérieure* Sér. 3(17), 21–86.

Bessembinder, H., & Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management* 27, 5–17.

Black, F. (1986). Noise. *The Journal of Finance* 41, 529-543.

Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. *The Journal of Finance* 49, 153–181.

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *The Journal of Finance,* 47, 1731–1764

Brorsen, B. W., & Irwin, S. H. (1987). Futures funds and price volatility. *The Review of Futures Markets* 6, 118–135.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance* 52, 57–82.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance* 51, 1681–1713.

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1999). The profitability of momentum strategies. *Financial Analysts Journal* 55, 80–90.

Cheung, Y. W., & Chinn, M. D. (2001). Currency traders and exchange rate dynamics: A survey of the U.S. market. *Journal of International Money and Finance* 20, 439–471.

Cornell, W. B., & J. K. Dietrich. (1978). The efficiency of the market for foreign exchange under floating exchange rates. *Review of Economics and Statistics* 60, 111–120.

Damodaran, A. (2002). *Investment valuation: Tools and techniques for determining the value of any asset*. John Wiley & Sons.

Fama, E. F. (1965a). The behavior of stock-market prices. *Journal of Business* 38, 34–105.

Fama, E. F. (1965b). Random walks in stock market prices. *Financial Analysts Journal* 21, 55–59.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance* 25, 383–417.

Fama, E. F., & Blume, M. E. (1966). Filter rules and stock market trading. *Journal of Business* 39, 226–241.

Fama, E. F., & French, K. R. (1992). The cross-section of expected returns. *The Journal of Finance* 47, 427–465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33, 3–56.

Grossman, S. J., & Stiglitz, J. E. (1976). Information and competitive price systems. *American Economic Review* 66, 246–253.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review* 70, 393–408.

Guidolin, M., & Timmermann, A. (2008). International asset allocation under regime switching, skew, and kurtosis preferences. *Review of Financial Studies* 21, 889–935.

Haas, M. (2007). Do investors dislike kurtosis? *Economics Bulletin* 7, 1–9.

Hsu, P.H., & Kuan, C.H. (2005). Re-examining the profitability of technical analysis with data snooping checks. *Journal of Financial Econometrics* 3, 606–628.

Irwin, S. H., & Uhrig, J. W. (1984). Do technical analysts have holes in their shoes? *Review of Research in Futures Markets* 3, 264–277.

Jensen, M. C., & Benington, G. A. (1970). Random walks and technical theories: Some additional evidence. *The Journal of Finance* 25, 469–482.

Kraus, A., & Litzenberger, R. (1976). Skewness preference and the valuation of risk assets. *The Journal of Finance* 31, 1085–1100.

Levy, H., & Sarnat, M. (1984). *Portfolio and investment selection: Theory and practice*. Prentice-Hall International: Englewood Cliffs, NJ.

Lo, A., & MacKinlay, A. C. (1990). Data snooping biases in tests of financial asset pricing models. *Review of Financial Studies* 3, 431–467.

Lo, A., Mamaysky, H., & Wang, J. (2000). Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation. *The Journal of Finance* 55, 1705–1765.

Lui, Y. H., & Mole, D. (1998). The use of fundamental and technical analyses by foreign exchange dealers: Hong Kong evidence. *Journal of International Money and Finance* 17, 535–545.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives* 17, 59–82.

Park, C-H, & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys* 21, 786–826.

Poole, W. (1967). Speculative prices as random walks: An analysis of ten time series of flexible exchange rates. *Southern Economic Journal* 33, 468–478.

Ready, M. J. (2002). Profits from technical trading rules. *Financial Management* 31, 43–61.

Roberts, H. (1967). Statistical versus clinical prediction of the stock market, Unpublished manuscript.

Samuelson, P. A. (1965). Proof that properly anticipated prices fluctuate randomly, *Industrial Management Review* 6, 41–49.

Shleifer A., & Summers, L. H. (1990). The noise trader approach to finance. *Journal of Economic Perspectives* 4, 19–33.

Stevenson, R. A., & Bear, R. M. (1970). Commodity futures: Trends or random walks? *The Journal of Finance* 25, 65–81.

Stewart, B. (1949). An analysis of speculative trading in grain futures. *Technical Bulletin* No. 1001, U.S. Department of Agriculture, Washington, D.C.

Sullivan, R., Timmermann, A., & White, H. (1999). Data snooping, technical trading rule performance, and the bootstrap. *The Journal of Finance* 54, 1647–1691.

Sweeny, R. J. (1986). Beating the foreign exchange market. *The Journal of Finance* 41, 163–182.

Taylor, M. P., & Allen, H. (1992). The use of technical analysis in the foreign exchange market. *Journal of International Money and Finance* 11, 304–314.

Treynor, J. L., & Black, F. (1973). How to use security analysis to improve portfolio selection. *Journal of Business* 46, 66–86.

Van Horne, J. C., & Parker, G. G. C. (1967). The random-walk theory: An empirical test. *Financial Analysts Journal* 23, 87–92.

White, H. (2000). A reality check for data snooping. *Econometrica* 68, 1097–1126.

Working, H. (1958). A theory of anticipatory prices. *American Economic Review* 48, 188–199.

Table 1. Importance of Technical Analysis to Managers of U.S. and International/Global Equity and Balanced Portfolios.

Technical Analysis Usage Ranking	**Investment Type**				**Total**
	U.S. Equity	**Intl./Global Equity**	**U.S. Balanced**	**Intl./Global Balanced**	
Very Important	3.3%	2.8%	3.4%	7.2%	3.3%
Important	7.7%	4.6%	3.4%	12.7%	6.9%
Utilized	21.3%	21.1%	7.1%	11.3%	20.2%
Not Important	14.4%	14.4%	4.3%	1.9%	13.4%
Not Utilized	53.3%	57.2%	81.8%	66.9%	56.2%
Observations	7,033	2,497	560	362	10,452

Note: This table reports the results of a 2012 survey of institutional portfolio managers' decision criteria. The particular survey question asks the extent to which technical analysis is important and used in the portfolio.

Table 2. Importance of Technical Analysis to Portfolio Managers, by Market Cap of Holdings.

Technical Analysis Usage Ranking	**Investment Capitalization for U.S. Equity Funds**				
	Large Cap	**Mid-Cap**	**Small Cap**	**Micro Cap**	**All Cap**
Very Important	2.9%	2.9%	2.3%	1.8%	5.9%
Important	7.8%	7.8%	6.2%	9.8%	9.1%
Utilized	21.8%	21.7%	21.1%	24.1%	20.1%
Not Important	14.0%	16.8%	16.7%	13.4%	11.1%
Not Utilized	53.4%	50.8%	53.8%	50.9%	53.8%
Observations	3,142	1,017	1,443	112	1,242

Note: This table reports the results of a 2012 survey of institutional portfolio managers' decision criteria. Respondents answered the degree to which technical analysis is important and used. Results are shown according to the market capitalization of portfolio holdings, with micro-cap firms having market value of equity (MVE) less than $500 million, small-cap firms MVE between $500 million-$2 billion, mid-cap firms MVE between $2 billion and $7 billion, and large-cap firms MVE over $7 billion.

Table 3. Pearson Correlation between Portfolio Managers' Usage of Technical Analysis and Other Decision Criteria.

Decision Criterion	**Correlation with Technical Analysis**
Momentum	0.378
Industry Sector Analysis	0.291
Theme Identification	0.283
Computer Screening/ Modeling	0.263
Top-Down	0.249
Earnings Surprise	0.243
Quantitative Research	0.223
Future Earnings Growth	0.194
Fundamental Analysis	0.107
Quality	0.102
Price to Cash	0.094
Return on Assets	0.090
Dividend Growth	0.075
Low Price to Sale	0.063
Dividend Yield	0.062
Cash Flow	0.058
Low Price to Earnings	0.056
Bottom-Up	0.035
Price to Book	0.032

Note: This table reports the correlation coefficient between portfolio managers' responses to survey questions about the extent to which technical analysis and other decision criteria are used. Qualitative survey responses are transformed to numerical form as follows: Technical analysis (and each of the other criteria in turn) is "Very Important" (5), "Important" (4), "Utilized" (3), "Not Important" (2), and "Not Utilized" (1). Correlations are listed from highest to lowest.

Table 4. Portfolio Managers' Rankings of Technical Analysis, by Primary Equity Decision Criterion.

	Technical Analysis Usage Ranking					
Primary Equity Decision Criterion	**Very Important**	**Important**	**Utilized**	**Not Important**	**Not Utilized**	**n**
Bottom-Up Stock Selection	2.1%	6.7%	22.9%	17.0%	51.4%	3,936
Quantitative/Research	4.6%	8.4%	17.7%	8.3%	61.0%	961
Fundamental Analysis	1.9%	8.2%	23.6%	16.7%	49.6%	831
Computer Screening/Models	3.7%	6.6%	16.4%	5.2%	68.1%	348
Top-Down/Economic Analysis	5.0%	17.9%	30.9%	13.9%	32.3%	201
Future Earnings Growth	8.9%	14.4%	25.6%	13.3%	37.8%	90
Theme Identification	4.6%	10.8%	36.9%	12.3%	35.4%	65
Low Price to Earnings	2.5%	7.5%	12.5%	27.5%	50.0%	40
Industry Sector Analysis	7.5%	32.5%	15.0%	7.5%	37.5%	40

Note: The rightmost column shows the number of portfolio managers who choose each of the listed criteria as their primary equity decision criterion. The table further reports the proportion of respondents in each row who indicate that technical analysis is very important, important, etc. to managing their portfolios. Primary equity decision criteria are listed in order from most to least frequently used.

Table 5. Monthly Performance of U.S. Institutional Portfolios, by Managers' Approach to Using Technical Analysis, January 1993-March 2012.

	Technical Analysis Usage Ranking					
Performance Measure	**Very Important**	**Important**	**Utilized**	**Not Important**	**Not Utilized**	**Statistic**
Observations	179	381	1,030	664	2,864	
Panel A. Raw Rate of Return						
Mean	0.99%	0.94%	0.94%	0.96%	0.95%	F = 4.01***
Median	1.35%	1.40%	1.52%	1.44%	1.48%	$\chi 2$ = 34.51***
Standard deviation	4.19%	4.47%	4.41%	4.33%	4.20%	F = 3.94***
Skewness	-0.49	-0.74	-0.81	-0.88	-0.88	
Kurtosis	1.33	1.44	1.68	2.20	2.20	
Panel B. Benchmark-adjusted Return						
Mean	0.27%	0.19%	0.17%	0.16%	0.18%	F = 4.01***
Median	0.23%	0.15%	0.16%	0.14%	0.16%	$\chi 2$ = 34.51***
Standard deviation	1.37%	0.75%	0.60%	0.47%	0.45%	F = 3.94***
Skewness	1.27	0.17	0.42	0.44	0.53	
Kurtosis	7.77	1.56	1.37	0.82	1.51	
Panel C. Information Ratio						
Mean	0.20	0.25	0.28	0.34	0.40	F = 5.48***

Note: This table shows average monthly performance results for U.S. equity managers according to the degree to which technical analysis is important and used. Equally weighted portfolio returns are calculated for each month, and then the summary statistics shown in the table are calculated over the 231 months between January 1993 and March 2012. The sample size listed in the top row is the maximum number of funds in the respective category. Not all funds were in existence throughout the performance period. The minimum number of funds reporting in any month were, respectively, 23, 54, 202, 127, and 358. Tests performed include ANOVA for differences among means and the Kruskal-Wallis test of equality of medians across the five technical-analysis usage rankings. A final test examines homogeneity of variances between the "Very Important" group and a combination of the "Not Important" and "Not Utilized" groups. Two and three asterisks, respectively, indicate 5% and 1% significance levels.

Table 6. Three and Four-Factor Alpha According to Managers' Approach to Using Technical Analysis, January 1993-March 2012

	Technical Analysis Usage Ranking					
	Very Important	**Important**	**Utilized**	**Not Important**	**Not Utilized**	**Statistic**
Observations	231	482	1,377	942	3,545	
					Three-Factor Alpha	
Mean	0.27	0.16	0.13	0.13	0.15	F = 7.38***
Median	0.12	0.11	0.01	0.11	0.12	$\chi 2$ = 12.02**
Standard Deviation	0.94	0.36	0.36	0.29	0.32	F = 8.93***
Skewness	9.22	1.20	1.49	0.34	0.66	
Kurtosis	108.56	13.91	15.08	5.03	8.75	
					Four-Factor Alpha	
Mean	0.24	0.13	0.11	0.12	0.14	F = 6.51***
Median	0.10	0.10	0.09	0.10	0.12	$\chi 2$ = 20.19***
Standard Deviation	0.98	0.35	0.34	0.28	0.31	F = 10.28***
Skewness	9.72	1.40	1.01	0.52	0.39	
Kurtosis	116.73	14.22	15.30	4.30	7.64	

Note: Three-factor alphas based on the Fama-French (1993) model and four-factor alphas based on the Carhart (1997) model are calculated for each institutional portfolio with at least 30 months of returns between January 1993 and March 2012. Tests performed include ANOVA for differences among means and the Kruskal-Wallis test of equality of medians across the five technical-analysis usage rankings. A final test examines homogeneity of variances between the "Very Important" group and a combination of the "Not Important" and "Not Utilized" groups. Two and three asterisks, respectively, indicate 5% and 1% significance levels.

Table 7. Monthly Rate of Return for Institutional Portfolios, Under Different Market Conditions, of Portfolio Managers Responding "Very Important" versus Those Responding "Not Utilized"

	Mean	**Median**	**Standard Deviation**	**Skewness**	**Kurtosis**
Panel A: Positive Market					
Very Important	3.42%	3.04%	2.53%	0.99	1.97
Not Utilized	3.38%	3.16%	2.27%	0.88	1.13
Panel B: Negative Market					
Very Important	-3.27%	-2.62%	2.98%	-1.70	4.51
Not Utilized	-3.31%	-2.37%	3.29%	-2.00	5.39
Panel C: Continuation					
Very Important	1.35%	1.99%	4.34%	-1.01	2.47
Not Utilized	1.32%	1.97%	4.41%	-1.37	3.48
Panel D: Reversal					
Very Important	0.51%	-0.13%	3.98%	0.35	0.09
Not Utilized	0.45%	0.19%	3.84%	-0.02	0.31

Note: This table shows monthly portfolio performance for funds that consider technical analysis to be very important versus those that do not use it, under differing market conditions between January 1993 and March 2012. The first (second) panel shows contemporaneous portfolio performance for months in which the S&P 500's returns were positive (negative). The third (fourth) panel reports contemporaneous performance in months when the previous one month's market return sign is continued (reversed). Tests performed include ANOVA for differences among means and the Kruskal-Wallis test of equality of medians across the five technical-analysis usage rankings. A final test examines homogeneity of variances between the "Very Important" group and a combination of the "Not Important" and "Not Utilized" groups.

Table 8. Monthly BAR, Under Different Market Conditions, for Portfolios of Investment Managers Responding "Very Important" versus those Responding "Not Utilized"

	Mean	**Median**	**Standard Deviation**	**Skewness**	**Kurtosis**
Panel A: Positive Market					
Very Important	0.11%	0.04%	1.49%***	1.59	9.33
Not Utilized	0.08%	0.09%	0.40%	0.01	1.02
Panel B: Negative Market					
Very Important	0.55%**	0.44%	1.09%***	0.51	0.14
Not Utilized	0.36%	0.29%	0.49%	0.74	0.96
Panel C: Continuation					
Very Important	0.27%	0.32%	1.26%***	0.35	2.54
Not Utilized	0.18%	0.21%	0.38%	0.38	0.78
Panel D: Reversal					
Very Important	0.27%	0.14%	1.51%***	1.99	11.11
Not Utilized	0.18%	0.14%	0.54%	0.59	1.19

Note: This table shows monthly portfolio performance net of benchmark for funds that consider technical analysis to be very important versus those that do not use it, under differing market conditions between January 1993 and March 2012. The first (second) panel shows contemporaneous portfolio performance for months in which the S&P 500's returns were positive (negative). The third (fourth) panel reports contemporaneous performance in months when the previous one month's market return sign is continued (reversed). Tests performed include ANOVA for differences among means and the Kruskal-Wallis test of equality of medians across the five technical-analysis usage rankings. A final test examines homogeneity of variances between the "Very Important" group and a combination of the "Not Important" and "Not Utilized" groups. Two and three asterisks, respectively, indicate 5% and 1% significance levels.

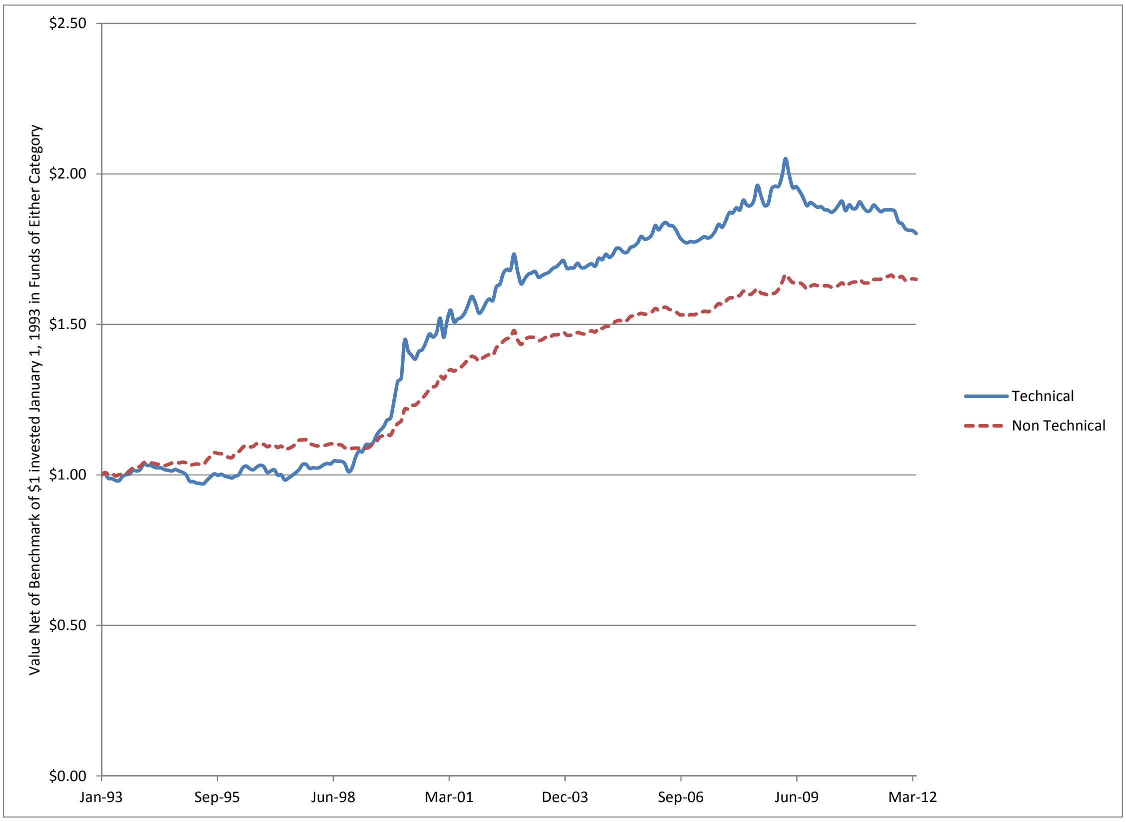

Fig. 1. Cumulative Return Net of Benchmark for Institutional Portfolios Using Technical Analysis vs. Funds that do not.

Note: This graph shows the cumulative value of $1 invested on January 1, 1993 in the average institutional portfolio managed using technical analysis versus the average portfolio matched on asset class, market capitalization, and primary equity investment style.