Literature Review

TECHNICAL ANALYSIS

Modern Perspectives

Gordon Scott, CMT, Michael Carr, CMT, and Mark Cremonie, CMT, CFA

CFA Institute Research Foundation

CMT Association

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Statement of Purpose

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ISBN 978-1-944960-11-7

November 2016

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CE Qualified Activity CFA Institute

This publication qualifies for 0.5 CE credits under the guidelines of the CFA Institute Continuing Education Program.

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Introduction

Technical analysis provides a framework for informing investment management decisions by applying a supply and demand methodology to market prices. Underlying principles of the study of technical analysis are derived from the assumption that changes in the supply and demand of traded securities affect their current market prices. Tools of technical analysis are built into a framework that seeks to gain insight from the changes in supply and demand. This framework has evolved over time from a purely visual analysis to more quantitative techniques. Like other analytical tools, technical analysis employs a disciplined, systematic approach that seeks to minimize the impact of behavioral biases and emotion from the practice of investment selection; consequently, many institutional analysts, strategists, and portfolio managers fuse technical research with other analytical approaches, such as quantitative, fundamental, and macroeconomic methods.

Independent researchers have confirmed the value of technical analysis, beginning with the confirmation of the momentum anomaly. Momentum, or relative strength in the vernacular of technical analysts, has been applied since at least the 1930s. It is now widely accepted that relative strength analysis can help investment managers achieve statistically and economically significant excess. Additional research has confirmed the value of other technical tools, including pattern analysis, moving averages, and indicators.

More recent research has addressed the role of technical analysis in the broader context of financial markets and begins to trace the linkages among behavioral economics, individual actors in financial markets, and the role of technical analysis in studying the behavior of individual actors. In this literature review, a number of those studies are referenced. The review also discusses the evolution of technical analysis and how that evolution, in the tradition of other social science disciplines, has served to address many of the criticisms of the field. This review demonstrates that, over time, ideas expressed by Charles Dow at the dawn of the 20th century have been validated in the 21st century. Researchers are now assessing the observations of analysts that built on Dow's theories, and technical analysts are applying this research to the market action in real time.

The idea that technical analysis has value as one tool among many in financial research finds strong support in scholarly literature as well as in the work of many practitioners. To show this support, we review recent publications and the work of a large group of practitioners on the topic of technical analysis in an institutional setting. The books and articles we cite are divided into three distinct groups: citations from technical analysis certification curricula, citations suggesting ways that technical analysis can be profitably integrated into investment selection methodologies, and recent citations that reflect a growing acceptance and validation of technical analysis.

In 2015, the Market Technicians Association (MTA), a worldwide professional association of technical analysis practitioners, conducted an extensive survey and analysis of job-related activity. The survey sought to identify how practitioners use technical analysis as part of their financial research activity and particularly what they considered the most critical knowledge and job skills involving technical analysis. This survey was part of the MTA's ongoing process of maintaining the curriculum readings for the three exam levels of the Chartered Market Technician (CMT), a FINRA (Financial Industry Regulatory Authority)-recognized designation for professionals in financial analysis. The survey sought to identify specific technical analysis knowledge and skills that were considered most valuable to practitioners today and, more specifically, what job tasks were performed using that knowledge and skill. This survey was the most comprehensive of its kind ever completed.

Analysis of the responses found that most practitioners did not use technical analysis in isolation but, rather, integrated their use of this analysis with other skills and knowledge. The responses also show that the approach used by practitioners is evolving over time. Nowadays, practitioners need an understanding of not only technical analysis but also aspects of other disciplines that can provide context for technical study. Based on insights from these responses, the exam curriculum was realigned to match the way that the discipline has evolved and to reflect the integration of technical analysis into financial research more generally. The redesigned curriculum draws on works that discuss not only technical analysis but also statistical analysis, quantitative analysis, behavioral finance, and fundamental analysis.

To help practitioners appreciate and understand the evolution of technical analysis as a modern discipline, the curriculum includes a treatment of the history, recent changes, and current practices in technical analysis. The curriculum also includes readings intended to help practitioners understand the issues that fostered resistance to this discipline in the financial industry. This information should help practitioners understand what practices improve the value of technical analysis, especially as the practice of technical analysis evolves in a manner that can be called "fusion analysis," or the inclusion of techniques from various disciplines in an integrated investment selection and decision-making model.

Because this effort was so comprehensive and conducted in a manner required by the development of psychometrically sound examinations, this review justifiably includes citations of the books and papers considered for inclusion in the readings for the CMT exams. This review also includes additional publications that contribute in significant ways to the understanding of how technical analysis can or does fuse with other disciplines in research activity. Finally, recent publications show the evolution of technical analysis toward a more robust and valuable body of knowledge and skill.

The Evolution of Technical Analysis

Over time, the general definition of technical analysis has remained constant. Technical analysis is the study of data generated by the action of markets and by the behavior and psychology of market participants and observers. Such study is usually applied to forecasting—that is, estimating the probabilities for the future course of prices for a market, investment, or speculation by interpreting the data in the context of precedent.

Technical analysis encompasses a variety of methods for turning past price histories into forecasts. In the late 1800s, the methods primarily involved creating charts that follow the "book method" as documented by Charles Dow and others.[1] This charting style is now called the "point and figure" method. More familiar bar charts were developed in the early 20th century, leading to pattern analysis becoming popular. Patterns were assigned varied names, but all served one of two purposes: identifying periods when markets were likely to begin a new trend or identifying periods of time when existing trends were likely to reverse. In other words, all patterns seek to define periods with a high probability of price consolidation or price reversal.

By the 1950s, charts were widely used, and moving averages, or automated trend lines, were being added to charts (Edwards, Magee, and Bassetti 2007). Seeking an edge, technical analysts in the 1960s were using more sophisticated mathematical techniques to calculate moving averages and other indicators. New moving averages include exponentially weighted averages as well as triangular weighted averages and other variations. In the end, each analyst was seeking an edge, but the different calculation methods did not resolve the problems involved with moving averages. High trading costs, delayed signals, and short-lived erroneous trading signals cause significant problems no matter how the average is calculated. Finding that more sophisticated math did not dramatically increase the effectiveness of moving averages, analysts created new indicators. Increased access to computers led to a proliferation of indicators, many of which rely on closing prices as their sole data series and subject closing prices to different forms of mathematical manipulation. Under quantitative testing, many of these indicators have not withstood the test of time or scrutiny of objective analysts, while some have been shown to add value to the investment selection process.

Advances in processing power and programming skills have allowed for objective testing of indicators and chart patterns. In recent years, quantitative

[1] Charles Dow, "Methods of Reading the Market," *Wall Street Journal* (20 July 1901).

analysis and behavioral finance have validated some of the techniques used by technical analysts. Standard financial theory has even embraced one of the most popular techniques: Relative strength analysis, as practiced by technical analysts, is closely related to the momentum anomaly in standard finance, although the difference in nomenclature may hide this relationship.

Criticisms of Technical Analysis

As Lo and Hasanhodzic note, technical analysis is a "legitimate and useful discipline, tarred by spurious associations and deserving of further academic studies" (p. 1).[2] Although it is easy to dismiss a discipline whose practitioners use visual analysis to detect head and shoulder patterns on charts, the patterns are often heuristics rather than random associations. Chart analysis is an intuitive approach to market prediction, sharing a goal with quantitative analysis—which is a statistical approach to market prediction—and with fundamental analysis, which relies on a careful study of financial statements to predict future returns. The means of reaching the goal are different in all three forms of analysis.

If the evolution of technical analysis had followed a traditional scientific process, as fundamental and quantitative analysis did, there would be less criticism of it. Instead, technical analysts have, at times, engaged in questionable practices. In the early days of technical analysis, many different theories were published and promoted—all sharing the problem that the causal or empirical link between the observations and the forecasts was loose or absent. As computer availability increased, testing to establish or reject such a link became commonplace. Early tests suffered from the problems of any study in the social sciences—the tests were often too narrow, the datasets were too small, and the results often could not be repeated. In the past, technical analysis lacked a formal approach to testing, verifying, and benchmarking different ideas. This lack of rigor led to wild debates around the efficacy of specific approaches that continues today.

As technical analysis has matured and computers have been used to automate the analysis, tools have been developed that allow for consistent verifying and benchmarking—such as comparing signals with the buy-and-hold performance of an index to evaluate whether excess returns are attainable with the signals. Although other financial analysts may have incorporated excess returns into their work earlier, technical analysts now commonly apply this approach.

A more valid criticism of technical analysis is that it is subjective. Although many analytical techniques require assumptions and, therefore, include some degree of subjectivity, the predictions of chartists (technical analysts who emphasize the visual interpretation of chart patterns in their work) are often viewed as completely subjective. Malkiel famously concluded

[2]Market Technicians Association, *CMT Level I 2016: An Introduction to Technical Analysis* (Hoboken, NJ: John Wiley & Sons, 2015).

"under scientific scrutiny, chart-reading must share a pedestal with alchemy" (p. 158).[3] In part, Malkiel reaches this conclusion by observing that a "chart derived from random coin tossings looks remarkably like a normal stock price chart and even appears to display cycles." Malkiel claims that because charts generated by coin tossings cannot be distinguished from actual price charts, neither chart has value.

Malkiel's point was the subject of a study by Hasanhodzic, Lo, and Viola (2010), who found that, when conditions simulate real-world trading, the two types of charts can be distinguished from each other. This test was designed

> to determine whether human subjects can differentiate between actual vs. randomized financial returns. The experiment consists of an online video-game where players are challenged to distinguish actual financial market returns from random temporal permutations of those returns. We find overwhelming statistical evidence (p-values no greater than 0.5%) that subjects can consistently distinguish between the two types of time series, thereby refuting the widespread belief that financial markets "look random." A key feature of the experiment is that subjects are given immediate feedback regarding the validity of their choices, allowing them to learn and adapt. (p. 1)

These test results do not argue against the criticism that individual results are subjective but demonstrate that charts can have value to skilled analysts.

Criticisms related to subjectivity can only be countered with objective analysis. Here the record is mixed. Some studies find that certain chart patterns can be used to generate excess profits. Other studies arrive at the opposite conclusion. Conflicting studies demonstrate the fact that there is a degree of subjectivity even in programming tests designed to identify subjectivity in analysis. In the end, this criticism must be accepted as being valid because there is a degree of subjectivity in pattern analysis, even when the analysis is done using automated rules. Less (or even no) subjectivity is found in indicator analysis, especially when studies follow standard testing protocols and evaluate the results against standard benchmarks.

[3]B.G. Malkiel, *A Random Walk Down Wall Street: The Time-Tested Strategy for Successful Investing* 6th ed. (New York: W.W. Norton & Company, 1996).

The Practice of Technical Analysis

Technical analysis has always focused on practical application, with technicians more focused on what works than why a particular strategy works. This distinction has been true since Charles Dow, informally known as the "grandfather of technical analysis," wrote editorials in the *Wall Street Journal* that would become the basis of Dow theory, a trend-following tool that is still widely used.

Dow theory was developed in the 1900s and derived solely from Dow's insights into the relationship between stock prices and the economy. Dow created his averages to track railroad and industrial stocks to potentially spot turning points in the business cycle. Dow theory provides buy and sell signals when both averages are moving in the same direction. Dow believed a major trend in the economy would result in major trends in the stock market. In a January 1902 editorial, he explained, "It is a bull period as long as the average of one high point exceeds that of the previous high points. It is a bear period when the low point becomes lower than the previous low points" (p. 154).[4] In a bull market, the market is expected to continue to move higher, and in a bear market, the market is expected to continue to move lower; in other words, in this analysis, "bull" and "bear" do not simply characterize past movements but also exploitable trends. Recent research (Dahlberg 2016) has demonstrated that this simple idea has delivered consistently profitable results over the years.

Although Dow's theory is simple enough to implement by observing higher highs and lower lows, analysts have always wanted to beat the market by as wide a margin as possible, leading to a search for ways to improve on simple techniques. One of the earliest quantitative approaches to investing was defined by Robert Rhea in a 1933 issue of *Barron's*. Rhea was also a student of Dow's theory and was the first to collect all of Dow's editorials and those of his successor at the *Wall Street Journal*, William Peter Hamilton, into a single volume published as *The Dow Theory*.[5]

Rhea also advanced the study of the market with original research. In a single, half-page article, "Stock Habits: A Simple Method to Follow Issues That Fluctuate More Widely Than the Averages," Rhea described how to

[4]Laura Sether, *Dow Theory Unplugged* (Cedar Falls, IA: W&A Publishing, 2009).
[5]Robert Rhea, *The Dow Theory: An Explanation of Its Development and an Attempt to Define Its Usefulness as an Aid in Speculation* (Burlington, VT: Fraser Publishing Company, 1994).

calculate an "appreciation index" for a group of stocks.[6] The appreciation index was the total return of the stock over the life of a bull or bear market. He showed that a group of stocks with the highest appreciation indexes outperformed a group of income stocks he created to serve as a benchmark. His test was simple by modern standards, but it appears to be the first quantified test of relative strength (RS).

In 1945, RS made its first appearance in an academic journal when H.M. Gartley, known more as a chartist than a quantitative analyst, introduced the world to velocity statistics as an investing tool in an article in the *Analysts Journal*:

> First it is necessary to select some average or index to represent the broad market, such as the Standard & Poor's 90-stock Index, the Dow-Jones 65-stock Composite, or a more comprehensive measure…
>
> By tracing back the fluctuation pattern of the general average, the larger swings are selected (by inspection) and the successive high and low points are then used to compute percentage advances and declines. Although the general market trend may make the choice of smaller movements feasible, usually the swings selected are those of 10% or more…
>
> The next step is to compute the comparable percentage advance or decline of the individual stock in the swing….And finally, the percentage rise or decline in the individual stock is divided by the corresponding move in the base index, and multiplied by 100, to give the "velocity rating" of the stock. (p. 64)[7]

Gartley's methods were similar to the technique Rhea presented in *Barron's*. Gartley identified major bull and bear trends within the overall market. He compared the movement of each individual stock with the movement of the overall market during each timeframe and calculated the velocity of each stock. His concept of velocity closely resembles beta in the capital asset pricing model. He advocated buying stocks with high velocity in bull markets.

After Gartley's work, RS largely disappeared from the literature for three decades before Robert Levy published "Relative Strength as a Criterion for Investment Selection" in the *Journal of Finance* in 1967.[8] Levy's work was the subject of a great deal of criticism after publication,[9] and again RS disappeared

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[6]Robert Rhea, "Stock Habits: A Simple Method to Follow Issues that Fluctuate More Widely than the Averages," *Barron's* (8 May 1933).

[7]H.M. Gartley, "Relative Velocity Statistics: Their Application in Portfolio Analysis," *Analysts Journa*l, vol. 1, no. 2 (April 1945): 60–64.

[8]Robert A. Levy, "Relative Strength as a Criterion for Investment Selection," *Journal of Finance,* vol. 22, no. 4 (December 1967): 595–610.

[9]Michael C. Jensen, "Random Walks: Reality or Myth—Comment," *Financial Analysts Journal,* vol. 23, no. 6 (November/December 1967): 77–85.

from the literature for almost 30 years. In 1993, the concept was rediscovered as momentum when the *Journal of Finance* published "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency" by Narasimhan Jegadeesh and Sheridan Titman.[10] That paper demonstrated that momentum could be used to consistently outperform the broad stock market.

> Trading strategies that buy past winners and sell past losers realize significant abnormal returns over the 1965-1989 period. For example, the strategy we examine in most detail, which selects stocks based on their past 6-months return and holds them for 6 months, realizes a compounded excess return of 12.01% per year average. Additional evidence indicates that the profitability of the relative strength strategies are not due to their systematic risk. The results of our tests also indicate that the relative strength profits cannot be attributed to lead-lag effects that result from delayed stock price reactions to common factors. The evidence is, however, consistent with delayed price reaction to firm-specific information. (p. 89)

Since then, a number of academic studies have demonstrated that the momentum anomaly works in international markets and under a variety of market conditions. Momentum, or relative strength, is a tool commonly combined with other selection techniques, forming the basis of what could be called "fusion analysis." Fusion analysts use whatever they believe works in their investment decision process, combining technical analysis with fundamental analysis, for example. Asness (1997) and others have written about the combination of value and momentum techniques.

Momentum can broadly be considered as a quantitative approach to trend following, a trading strategy designed to benefit from extended market moves. This approach is similar to the ideas defined in Dow theory, which generates trading signals only after a trend is well underway. Dow's work also branched off into the study of cycles, based on Dow's interest in the work of the British economist William Stanley Jevons, who documented a cycle lasting approximately 10 years in a number of commodity prices. Dow extended the concept, arguing that Jevons' cycle could be divided into two approximately equal periods of boom and bust in the economy. Because Jevons' work was largely based on sunspot activity, other cycle analysts sought to identify market cycles based on natural phenomena. Famously, Ralph N. Elliott (of the "Elliott wave") and W.D. Gann developed theories that gained popularity and continue to hold sway over some adherents today. Cycle analysts

[10]Narasimhan Jegadeesh and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance*, vol. 48, no. 1 (March 1993): 65–91.

currently use tools, including fast Fourier transform (Sornette, Johansen, and Bouchaud 1996) or spectral analysis (Dyka, Dudojć, and Garus 2013).

Although sophisticated techniques are increasingly used in the practice of technical analysis, technicians remain loyal to the study of charts. Since at least the 1920s, chart pattern analysis has been in widespread use. In the period before markets were regulated by the US Securities and Exchange Commission, charts provided one of the few sources of reliable information available to traders. Patterns became popular subjects of analysis as traders looked for telltale signs of market manipulation, which was believed to be common. Forbes editor Richard Schabacker catalogued a number of patterns in *Stock Market Theory and Practice* in 1930. Other works expanded on the identification and use of patterns, but the first objective testing of patterns seems to have been published in 1995. In that year, researchers at the Federal Reserve Bank of New York published "Head and Shoulders: Not Just a Flaky Pattern":

> This paper evaluates rigorously the predictive power of the head-and-shoulders pattern as applied to daily exchange rates. Though such visual, nonlinear chart patterns are applied frequently by technical analysts, our paper is one of the first to evaluate the predictive power of such patterns. We apply a trading rule based on the head-and-shoulders pattern to daily exchange rates of major currencies versus the dollar during the floating rate period (from March 1973 to June 1994). We identify head-and-shoulders patterns using an objective, computer-implemented algorithm based on criteria in published technical analysis manuals. The resulting profits, replicable in real-time, are then compared with the distribution of profits for 10,000 simulated series generated with the bootstrap technique under the null hypothesis of a random walk. (p. 1)[11]

They concluded:

> Results: The head-and-shoulders trading rule appears to have some predictive power for the German mark and yen but not for the Canadian dollar, Swiss franc, French franc, or pound. Nonetheless, if one had speculated in all six currencies simultaneously, profits would have been statistically and economically significant. Taken individually, profits in the markets for yen and marks are also substantial when adjusted for transaction costs, interest differentials, or risk. These results are robust to changes in the parameters of the head-and-shoulders identification algorithm, changes in the sample period, and the assumption that exchange rates follow a GARCH process rather than a random walk. These results are

[11]C.L. Osler and P.H. Kevin Chang, "Head and Shoulders: Not Just a Flaky Pattern," Federal Reserve Bank of New York, Staff Report No. 4 (August 1995): www.newyorkfed.org/medialibrary/media/research/staff_reports/sr4.pdf.

> inconsistent with virtually all standard exchange rate models, and could indicate the presence of market inefficiencies. (p. 2)

Subsequent work (Bulkowski 2005, for example) has reached similar conclusions. Pattern analysis can generate significant profits under some circumstances. In part, because pattern analysis is not consistently reliable, technical analysts continued searching for tools that could improve their results. In their search for tradable advantages, technical analysts have added volume and breadth analysis to their work. The search for more powerful tools accelerated when computers simplified the process of creating new indicators, which led to data mining in many cases.

Data mining is another criticism of technical analysis. Many indicators and techniques have been developed by searching historical data for patterns. For example, an analyst may test all moving-average lengths from 1 day to 10,000 days to find the most profitable moving average to use (actually, the most profitable one to have used over the past period being tested). They might then add additional conditions, such as a second or third moving average. Because so many variables are tested, the results are not a reliable indicator of future performance. Some bad results are due to statistically flawed testing, and other results are simply the result of sheer luck. For this reason,

> Profitable past performance is not taken at face value but rather evaluated in light of the possibility that back-test profits can occur by sheer luck. The problem of lucky performance is especially pronounced when many methods are back-tested and a best method is selected. This activity is called data mining. Though data mining is a promising approach for finding predictive patterns in data produced by largely random complex processes such as financial markets, its findings are upwardly biased. This is the data mining bias. Thus, the profitability of methods discovered by data mining must be evaluated with specialized statistical tests designed to cope with the data mining bias.[12]

[12]David Aronson, "Evidence Based Technical Analysis Trading Stocks Commodities" (2006): www.evidencebasedta.com.

Modern Applications of Technical Analysis

Recognition of the data mining bias has led to more objective applications of technical analysis. In recent years, the MTA has recognized this change by adding readings on statistics and quantitative analysis to its CMT program. FINRA gave its official recognition to the CMT as a financial professional designation in 2005. But it may well be that the academic community was the first to recognize this shift toward a more professional approach to technical analysis.

Financial markets have been the subject of academic research since at least 1900, when Louis Bachelier published his PhD dissertation *Théorie de la speculation*, which discussed the use of Brownian motion to model prices in the financial market. A study of Dow's theory was undertaken by Alfred Cowles in 1934.[13] Cowles found that the trend-following strategy would have earned less than a buy-and-hold strategy. In contrast, a more recent review of that work (Brown, Goetzmann, and Kumar) concluded that the Dow theory portfolio produced higher risk-adjusted returns.[14] When risk is considered, Brown et al. concluded that a portfolio following the Dow theory editorials would have had a higher Sharpe ratio than a buy and hold portfolio (0.559 compared with 0.456) and a positive Jensen measure of 4.04%.

Other areas of technical analysis have also been subjected to rigorous study, often with mixed results. In one study, moving averages (Brock, Lakonishok, and LeBaron) were found to be effective:

> This paper tests two of the simplest and most popular trading rules—moving average and trading range break, by utilizing a very long data series, the Dow Jones index from 1897 to 1986. Standard statistical analysis is extended through the use of bootstrap techniques. Overall our results provide strong support for the technical strategies that are explored. The returns obtained from buy (sell) signals are not consistent with the three popular null models: the random walk, the AR(I) and the GARCH-M. Consistently, buy signals generate higher returns than sell signals. Moreover, returns following sell signals are negative which is not easily explained by any of the currently

[13]Alfred Cowles, "Can Stock Market Forecasters Forecast?" *Econometrica*, vol. 1, no. 3 (July 1933): 309–324.

[14]Stephen J. Brown, William N. Goetzmann, and Alok Kumar, "The Dow Theory: William Peter Hamilton's Track Record Reconsidered," *Journal of Finance,* vol. 53, no. 4 (August 1998): 1311–1333.

> existing equilibrium models. Furthermore, the returns following buy signals are less volatile than returns following sell signals. (p. 1731)[15]

Specifically, this study found:

> The results generally show that returns during buy periods are larger and less volatile than returns during sell periods. For example, the variable length moving average produced on average a daily return for buy periods of 0.042 percent which is about 12 percent at an annual rate. The corresponding daily return for the sell periods is -0.025 percent which is about -7 percent at an annual rate. (p. 1733)

Although this study supports the idea that technical analysis works, it may be guilty of the data mining bias. Even though only two rules were tested, numerous parameters and filters were tested to find the values that provided the best results. In all, 7,846 different technical trading rules were studied.

Sullivan, Timmermann, and White reviewed this study to evaluate whether data mining presented problems. They concluded that the process used did not present a problem, but they noted, " . . . It is possible that, historically, the best technical trading rule did indeed produce superior performance, but that, more recently, the markets have become more efficient and hence such opportunities have disappeared" (p. 1675).[16]

A subsequent study (Fang, Jacobsen, and Qin) seems to confirm that the simple moving-average rules may no longer be effective based on an out-of-sample test:

> In a true out of sample test we find no evidence that several well-known technical trading strategies predict stock markets over the period of 1987 to 2011. Our test is free of the sample selection bias, data mining, hindsight bias, or any of the other usual biases that may affect results in our field. We use the exact same technical trading rules that Brock, Lakonishok and LeBaron (1992) showed to work best in their historical sample. Further analysis shows that this poor out-of-sample performance most likely is not due to the market becoming more efficient—instantaneously or gradually over time—but probably a result of bias. (p. 30)[17]

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[15]William Brock, Josef Lakonishok, and Blake LeBaron, "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns," *Journal of Finance,* vol. 47 no. 5 (December 1992): 1731–1764.

[16]Ryan Sullivan, Allan Timmermann, and Halbert White, "Data-Snooping, Technical Trading Rule Performance, and the Bootstrap," *Journal of Finance,* vol. 54, no. 5 (October 1999): 1647–1691.

[17]Jiali Fang, Ben Jacobsen, and Yafeng Qin, "Predictability of the Simple Technical Trading Rules: An Out-of-Sample Test," *Review of Financial Economics,* vol. 23, no. 1 (January 2014): 30–45.

Other researchers have explored more sophisticated techniques. Conrad and Kaul took this approach:

> In this article we use a single unifying framework to analyze the sources of profits to a wide spectrum of return-based trading strategies implemented in the literature. We show that less than 50 percent of the 120 strategies implemented in the article yield statistically significant profits and, unconditionally, momentum and contrarian strategies are equally likely to be successful. However, when we condition on the return horizon (short, medium, or long) of the strategy, or the time period during which it is implemented, two patterns emerge. A momentum strategy is usually profitable at the medium (2- to 12-month) horizon, while a contrarian strategy nets statistically significant profits at long horizon, but only during the 1926-1947 sub-period. More importantly, our results show that the cross-sectional variation in the mean returns of individual securities included in these strategies plays an important role in their profitability. The cross-sectional variation can potentially account for the profitability of momentum strategies and it is also responsible for attenuating the profits from price reversals to long-horizon contrarian strategies. (p. 489)[18]

By introducing the concept of the return horizon to their study, Conrad and Kaul's study recognizes that technical traders are not a homogenous group. This observation has important practical implications for traders. Their findings can be restated as follows: Trend following and momentum strategies are more likely to deliver gains for long-term traders, while short-term traders are more likely to attain success with mean-reversion strategies. In practice, the importance of the time horizon at least partly explains the popularity of oscillators (popular technical indicators, such as RSI and stochastics) among short-term traders and the use of moving averages (a trend-following tool) and relative strength strategies among traders with a longer time horizon.

As studies continued to be published, the number of conflicting results appeared to grow. A review (Park and Irwin) summarized the results of a number of other studies:

> [T]he number of studies that identified profitable technical trading strategies is far greater than the number of studies that found negative results. Among a total of 92 modern studies, 58 studies found profitability (or predictability) in technical trading strategies, while 24 studies reported negative results. The rest (10 studies) indicated mixed results. In every market, the number of profitable studies is twice that of unprofitable studies. However, modern studies also indicated that technical trading strategies had been able to yield economic profits in US stock markets until the late 1980s, but not thereafter

[18]Jennifer Conrad and Gautam Kaul, "An Anatomy of Trading Strategies," *Review of Financial Studies,* vol. 11, no. 3 (July 1998): 489–519.

> (Bessembinder and Chan 1998; Sullivan, Timmermann, and White 1999; Ready 2002). Several studies found economic profits in emerging (stock) markets, regardless of sample periods considered (Bessembinder and Chan 1995; Ito 1999; Ratner and Leal 1999). For foreign exchange markets, it seems evident that technical trading strategies have made economic profits over the last few decades, although some studies suggested that technical trading profits have declined or disappeared in recent years (Marsh 2000; Neely and Weller 2001; Olson 2004). For futures markets, technical trading strategies appeared to be profitable between the mid-1970s and the mid-1980s. No study has yet comprehensively documented the profitability of technical trading strategies in futures markets after that period. (p. 55)[19]

Practitioners are likely to agree with the conclusion that simple technical trading rules will not usually result in profits. For this reason, practicing technical analysts generally apply multiple techniques rather than the simple rules that are widely studied; thus, their results can differ from the results seen in studies. They often, for example, combine relative strength or momentum with value methods in a fusion analysis model. Limiting the universe of possible investments to value stocks is a step taken to limit risk under this model.

[19]Cheol-Ho Park and Scott H. Irwin, "The Profitability of Technical Analysis: A Review," AgMAS Project Research Report No. 2004-04 (October 2004): http://ssrn.com/abstract=603481.

Recent Research

As technical analysts sought new strategies to profit from market moves, researchers sought new theories to explain the reason behind the moves. These searches intersect at several points.

Notably, Lo's adaptive market hypothesis (AMH) views markets as less of a structure built on neoclassical economic theory and more of an evolutionary system. Lo proposes a biological view of the markets instead of one based on physical laws. Under this model, individuals, acting in their own interest, make mistakes rather than acting perfectly rationally at all times. Individuals learn from their past actions and adapt their actions in the future to reflect the knowledge they have acquired. This framework incorporates evolutionary concepts—including competition, innovation, and natural selection—and demonstrates that markets will move between irrational and efficient extremes.[20]

This approach is similar to research done at the Santa Fe Institute, a research organization pursuing cross-disciplinary studies of complex systems, including economies and stock markets. Among the research produced by the Santa Fe Institute are papers bridging the gap between economic theory and financial markets, such as "An Empirical Behavioral Model of Price Formation" (Mike and Farmer), in which they explain:[21]

> Although behavioral economics has demonstrated that there are many situations where rational choice is a poor empirical model, it has so far failed to provide quantitative models of economic problems such as price formation. We make a step in this direction by developing empirical models that capture behavioral regularities in trading order placement and cancellation using data from the London Stock Exchange. For order placement we show that the probability of placing an order at a given price is well approximated by a Student distribution with less than two degrees of freedom, centered on the best quoted price. This result is surprising because it implies that trading order placement is symmetric, independent of the bid-ask spread, and the same for buying and selling. We also develop a crude but simple cancellation model that depends on the position of an order relative to the best price and the imbalance between buying and selling orders in the limit order book. These results are combined to construct a stochastic representative agent model, in which the orders and cancellations are described in terms of conditional probability distributions. This model is used to simulate

[20]Andrew W. Lo, "The Adaptive Markets Hypothesis," *Journal of Portfolio Management,* vol. 30, no. 5 (September 2004): 15–29.

[21]Szabolcs Mike and J. Doyne Farmer, "An Empirical Behavioral Model of Liquidity and Volatility," undated working paper (http://ssrn.com/abstract=1011403).

> price formation and the results are compared to real data from the London Stock Exchange. Without adjusting any parameters based on price data, the model produces good predictions for the magnitude and functional form of the distribution of returns and the bid-ask spread. (p. 1)

By identifying mathematical models of order placement, this work demonstrates that price action provides meaningful information to market participants. Other work demonstrates that market participants adapt to the information the market provides and react to prices rather than just the opposite, when fundamental and economic factors affect prices.

Farmer also found that actual markets can be duplicated with models that include a variety of traders.[22] His evolutionary model included value investors, technical traders, liquidity traders, and market makers. Their interactions in computer simulations mirrored market action seen in real markets:

> Markets have internal dynamics leading to excess volatility and other phenomena that are difficult to explain using rational expectations models. This paper studies these using a nonequilibrium price formation rule, developed in the context of trading with market orders. Because this is so much simpler than a standard inter-temporal equilibrium model, it is possible to study multi-period markets analytically. There price dynamics have second order oscillatory terms. Value investing does not necessarily cause prices to track values. Trend following causes short term trends in prices, but also causes longer-term oscillations. When value investing and trend following are combined, even though there is little linear structure, there can be boom-bust cycles, excess and temporally correlated volatility, and fat tails in price fluctuations. The long term evolution of markets can be studied in terms of flows of money. Profits can be decomposed in terms of aggregate pairwise correlations. Under reinvestment of profits this leads to a capital allocation model that is equivalent to a standard model in population biology. An investigation of market efficiency shows that patterns created by trend followers are more resistant to efficiency than those created by value investors, and that profit maximizing behavior slows the progression to efficiency. Order of magnitude estimates suggest that the timescale for efficiency is years to decades. (p. 895)

Farmer's finding is that markets function through the interactions of various types of traders. Markets would not operate in the way we are familiar with unless value investors, technical investors, liquidity traders, and market makers are present.

The AMH and evolutionary theories of markets predict that some investment techniques will work at times and be ineffective at other times as traders

[22]J. Doyne Farmer, "Market Force, Ecology and Evolution," *Industrial and Corporate Change*, vol. 11, no. 5 (November 2002): 895–953.

adapt to their current environment. This conclusion is supported by research that finds technical analysis is effective at times and in some markets and ineffective at other times.

In recent years, in the foreign exchange markets, researchers have concluded technical analysis can provide profitable results:

> In particular, we conclude that technical analysis indeed has predictive power for both developed and emerging currencies, in terms of being able to generate significant mean excess returns and impressive Sharpe ratios, but that emerging market currencies are in general more predictable with technical analysis than are developed country currencies. Moreover, this excess profitability is not in general wiped out when realistic allowance is made for transaction costs, although the profitability of technical analysis among both emerging market and developed country currencies does appear to have been declining over time. These general findings were also supported by an out-of-sample analysis, which in particular revealed the very impressive performance of technical analysis for some emerging market currencies during the out-of-sample period 2012-2015. (p. 226)[23]

Recent tests of the effectiveness of momentum strategies are less favorable:

> We evaluate the robustness of momentum returns in the US stock market over the period 1965 to 2010. We find that momentum profits have become insignificant since the late 1990s partially driven by pronounced increase in the volatility of momentum profits in the last 12 years. Past returns no longer explain the cross-sectional variation in stock returns, not even following up markets. The patterns in the post holding period returns of momentum portfolios and risk adjusted identification period buy and hold returns of stocks in momentum supports improvement in market efficiency as a possible explanation for the declining momentum profits. (p. 1)[24]

It is possible that additional research or changes in market structure will find momentum has returned to profitability. It is also possible that continued research will confirm different techniques work at different times in the markets.

[23]Po-Hsuan Hsu, Mark P. Taylor, and Zigan Wang, "Technical Trading: Is It Still Beating the Foreign Exchange Market?" *Journal of International Economics*, vol. 102 (September 2016): 188–208.

[24]Debarati Bhattacharya, Raman Kumar, and Gokhan Sonaer, "Momentum Loses Its Momentum: Implications for Market Efficiency," Midwest Finance Association 2012 Annual Meetings Paper (7 November 2012): http://ssrn.com/abstract=1928764.

Conclusion

Academic research identifying the relationship between markets and market participants may provide the rationale for technical analysis. As research continues in this field, technical analysts are relentlessly working to improve their research techniques in pursuit of finding what works. On occasion, these fields of study intersect.

Recent research (Northington and Dahlberg 2016) identifies a technical indicator known as volatility-based support resistance (VBSR). Support and resistance are important concepts from chart-based pattern analysis. These levels are price areas on charts where buying or selling is expected to develop with sufficient pressure to reverse the direction of the trend. Support and resistance are believed to be developed based on investor psychology and are sometimes explained in terms of loss aversion. VBSR quantifies volatility extremes based on recent price action and uses those extremes to identify expected future support or resistance levels (quantifiable volatility extremes). This indicator uses classical technical analysis principles to forecast support and resistance levels. It differs from classical technical analysis by using advanced mathematical calculations to identify the price levels. In this way, the work is reproducible and testable. It is also explainable with standard finance theory. Implied volatility, an important component of some pricing models, exhibits a statistical tendency toward mean reversion. VBSR exploits this tendency to develop a statistical forecasting model.

Recent advances in software and programming allow this indicator (and all indicators) to be tested in novel ways for technical analysis.[25] By applying event testing principles to indicator signals, the statistical validity of the signal can be evaluated. This method, combined with an analysis of excess returns, may bridge the gap between the theory and practice of technical analysis. Early tests using these techniques are demonstrating that many widely used technical indicators do not generate profits on their own. More advanced techniques, such as VBSR, do enhance profitability. It is likely that continued research will find a variety of tools that exploit market inefficiencies with technical indicators, a feat that is entirely possible under the AMH and other advanced theories.

[25] See www.optuma.com.

References

Publications Reviewed for the Revised CMT Curriculum

Aronson, D.R. 2006. *Evidence-Based Technical Analysis: Applying the Scientific Method and Statistical Inference to Trading Signals*. Chichester, UK: John Wiley & Sons.

This text makes an important contribution to technical analysis literature because it clearly articulates the difference between subjective and objective methods in technical analysis. This distinction is not only important to new practitioners but also to experienced analysts and professionals who want to understand how this form of analysis has modernized. *Evidence-Based Technical Analysis* examines how technical analysis researchers should apply scientific methods and statistical tests to determine the true effectiveness of technical trading signals.

Bauer, Richard J., and Julie R. Dahlquist. 1998. *Technical Market Indicators: Analysis and Performance*. Hoboken, NJ: John Wiley & Sons.

"*Technical Market Indicators* is a unique study of the performance of many widely…used technical analysis indicators. The authors explore in an unbiased, rigorous manner whether these indicators consistently perform well or fail to do the job. The book provides description and data from comprehensive testing of sixty different indicators." Test results include "a large sample of stocks over a twelve-year time period, encompassing varying market conditions. Instead of using the traditional technical analysis charts, this detailed analysis takes a different approach, calculating numbers based on various relationships and letting the numbers dictate the decisions. This allows the investor to consider the value of these technical methods without consulting a chart." (p.1)

The authors address views both for and against the use of technical analysis and attempt to shed additional light onto the controversy through their systematic testing. They summarize their findings with a number of timeless conclusions that set the standard for how technical analysis tools can be expected to best add value in research efforts.

Bulkowski, Thomas N. 2005. *Encyclopedia of Chart Patterns*, 2nd ed. Hoboken, NJ: John Wiley & Sons.

Bulkowski provides statistics for both bull and bear markets. The book suggests how analysts can trade based on quarterly earnings announcements, retail sales, and stock upgrades and downgrades and provides back-testing evidence to support conclusions.

Bulkowski, Thomas N. 2008. *Encyclopedia of Candlestick Charts*. Chichester, UK: John Wiley & Sons.

Thomas Bulkowski provides examples of candlestick formations, identification guidelines, and statistical analysis of detailed trading tactics. *Encyclopedia of Candlestick Charts* gives analysts the correct tools for candlestick identification.

Burton, Edwin T., and Sunit N. Shah. 2013. *Behavioral Finance: Understanding the Social, Cognitive, and Economic Debates*. Hoboken, NJ: John Wiley & Sons.

University of Virginia professor Edwin Burton and industry practitioner Sunit Shah collect a concise articulation of behavioral finance issues. Their treatment is particularly germane to technical analysis practitioners because they indicate where they place technical traders in the context of the efficient market hypothesis. Additional topics include research into psychological behavior pioneered by Daniel Kahneman and Amos Tversky and serial correlation patterns in stock price data. The text facilitates thought about practical applications of behavioral finance in the use of technical analysis.

Ciana, Paul. 2011. *New Frontiers in Technical Analysis: Effective Tools and Strategies for Forecasting and Trading*. Hoboken, NJ: John Wiley & Sons.

The single chapter from this book that specifically focuses on relative rotational graphs was included in the CMT curriculum. This is a novel adaptation of relative strength investing, which creates a circular graph. This visualization is unique in its approach and has shown evidence of identifying unusual market activity.

Colby, Robert W. 2002. *The Encyclopedia of Technical Market Indicators*, 2nd ed. New York: McGraw-Hill Education.

The Encyclopedia of Technical Market Indicators provides a listing of important indicators, descriptions of the indicators, and statistical results they produced. Practitioner Robert Colby defines what each indicator is, explains the philosophy behind the indicator, and provides guidelines for using the selection techniques. The book tests different indicators on a cross-comparable basis as well. This book was more exhaustive than necessary for the curriculum but was considered a standard of quality against which other curriculum entries should be compared.

Davis, Ned. 2014. *Being Right or Making Money*, 3rd ed. Hoboken, NJ: John Wiley & Sons.

Ned Davis, founder of Ned Davis Research, articulates the basic components of a model for active investing decisions. The time-tested principles in this book guide practitioners to identify different classes of data and indicators to work from so that any investing model is not built from redundant information repackaged in different ways. The book provides information on "how to create asset allocation models in both stocks and bonds, how to make sense out of contrarian opinion, and how to use indicators" to better aid selection decisions.

Edwards, Robert D., John Magee, and W.H.C. Bassetti. 2013. *Technical Analysis of Stock Trends,* 10th ed. Boca Raton, FL: Taylor & Francis.

Technical Analysis of Stock Trends was the first book to produce a methodology for interpreting the predictable behavior of investors and markets. For over a decade, the book was part of the MTA's reading list for the CMT exams. The book has been updated with its 10th edition and is regarded as having been influential for decades among technical analysis practitioners.

Katsanos, Markos. 2008. *Intermarket Trading Strategies*. Chichester, UK: John Wiley & Sons.

The text explains "how to use Intermarket Analysis to forecast future equity, index, and commodity price movements" in mathematically sound ways. Katsanos' book helps practitioners identify indicators and viable intermarket based systems for use in trading systems or actively managed portfolios. The selection techniques can be used for long-term, intermediate, and short-term trading.

Kaufman, Perry J. 2013. *Trading Systems and Methods + Website*, 5th ed. Hoboken, NJ: John Wiley & Sons.

This book presents an analytical framework for comparing systematic methods and techniques. The text covers trends, momentum, arbitrage, integration of fundamental statistics, and risk management. The book describes how each technique can be used by an analyst to recognize similarities and variations that may serve as valuable selection techniques. The book also walks readers through basic mathematical and statistical

concepts of trading system design and methodology, such as how much data to use, how to create an index, and how to apply risk measurements.

Kirkpatrick, Charles D., and Julie R. Dahlquist. 2015. *Technical Analysis: The Complete Resource for Financial Market Technicians,* 3rd ed. Upper Saddle River, NJ: FT Press.

This book:

"systematically explains the theory of technical analysis, presenting academic evidence both for and against it…. Using hundreds of fully updated illustrations…, the authors explain the analysis of both markets and individual issues, and present complete investment systems and portfolio management plans. They present…up-to-date coverage of tested sentiment, momentum indicators, seasonal affects, flow of funds, testing systems, risk mitigation strategies, and many other topics. [This edition] thoroughly covers the latest advances in pattern recognition, market analysis, and systems management." (p. 1)

The authors introduce new confidence tests; cover increasingly popular indicators; present innovations in exit stops, portfolio selection, and testing; and discuss the implications of behavioral bias for technical analysis. They also reassess old formulas and methods (such as intermarket relationships), identifying pitfalls that emerged during the recent market decline. This text is widely considered the single best text for explaining the practical use of technical analysis concepts.

Lo, Andrew W., and Jasmina Hasanhodzic. 2010. *The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals*. Hoboken, NJ: John Wiley & Sons.

MIT finance professor Andrew W. Lo and coauthor Jasmina Hasanhodzic describe where technical analysis began and indicate how its use has changed over time. The book's first five chapters, included in the CMT curriculum, are not only an accurate retelling but also an interesting example of the adaptive market hypothesis in action. Whether the methods and measures are "driven by mass psychology, fear or greed of investors, the forces of supply and demand, or some combination of these, technical analysis has flourished for thousands of years" in its attempt to measure the unknown forces on the markets. In *The Evolution of Technical Analysis: Financial Prediction from Babylonian Tablets to Bloomberg Terminals*, the authors explain "how the charting of past stock prices for the purpose of identifying trends, patterns, strength, and cycles within market data has

allowed traders to make informed investment decisions based in logic, rather than on luck" (p. 1).

Montier, James. 2007. *Behavioural Investing: A Practitioners Guide to Applying Behavioural Finance*. Chichester, UK: John Wiley & Sons.

In this book, practitioner James Montier explores the biases often found in the investment process. The author shows analysts how to adopt an empirically based, skeptical approach to investing. The book combines "insights from applied psychology with a thorough understanding of the investment problem. The content is practitioner focused throughout and is helpful for any investment professional looking to improve their investing behavior to maximize returns" (p. 1).

Rhoads, Russell. 2011. *Trading VIX Derivatives: Trading and Hedging Strategies Using VIX Futures, Options, and Exchange Traded Notes*. Chichester, UK: John Wiley & Sons.

This book describes the volatility index (VIX). Also:

"known as the fear index, the VIX provides a snapshot of expectations about future stock market volatility and generally moves inversely to the overall stock market. *Trading VIX Derivatives* shows how to use the Chicago Board Options Exchange's S&P 500 volatility index to gauge fear and greed in the market, use market volatility [as an] advantage, and hedge stock portfolios. [The book] explains the mechanics and strategies associated with trading VIX options, futures, exchange traded notes, and options on exchange traded notes." (p. 1)

Rhoads articulates how technical analysts can look at the VIX to help understand market sentiment and anticipate changes in price trends.

Weigand, Robert A. 2014. *Applied Equity Analysis and Portfolio Management: Tools to Analyze and Manage Your Stock Portfolio + Online Video Course*. Hoboken, NJ: John Wiley & Sons.

Three chapters from this text are tapped to concisely provide a framework for portfolio management issues. These chapters provide perspective on active money management, a framework for analyzing the macro environment, and tools for attributing portfolio performance. These texts enable practitioners to recognize what context technical analysis must work within to maximize its contribution to effective research and analysis. The text prepares candidates who may pursue work in "creating and interpreting outputs typically associated with a top-down money management shop — including a macroeconomic forecasting newsletter, detailed stock research reports, and a portfolio performance attribution analysis." (p. 1)

Williams, Jason. 2012. *The Mental Edge in Trading: Adapt Your Personality Traits and Control Your Emotions to Make Smarter Investments*. New York: McGraw-Hill Education.

Although this book is not about charts, it is an important work in understanding the application of technical analysis for trading. It studies the behavioral aspects of trading by conducting a clinical look at people who actively trade with charts and who have had substantial success in doing so. The book identifies a "critical link between successful trading and personality traits." A psychiatrist, Dr. Jason Williams interviewed and studied unusually successful traders who managed millions or billions of dollars to see what personality traits, if any, could be found to explain their success. This book may provide an important link for understanding how some traders overcome natural human biases described in many behavioral finance studies and find unusual success in trading while using technical analysis.

Williams, Larry. 2011. *Long-Term Secrets to Short-Term Trading*, 2nd ed. Chichester, UK: John Wiley & Sons.

Unusually successful trader Larry Williams highlights the advantages and disadvantages of short-term trading. The author points out that such trading can be a "very fruitful yet potentially dangerous endeavor." He gives a nod to the efficient market hypothesis, yet challenges its conclusions based on his own considerable experience and observations. The text offers insight on a "wide range of topics, including chaos, speculation, volatility breakouts, and profit patterns [and] explains fundamentals such as how the market moves, the three most dominant cycles, when to exit a trade, and how to hold on to [profitable positions]" (p. 1). The book "includes in-depth analysis of the . . . short-term trading strategies" the author has found to be most successful. This text is under consideration for inclusion in future curriculum readings.

Publications Featuring Support for Integrated Technical Analysis and Fusion Analysis

Asness, Clifford S. 1997. "The Interaction of Value and Momentum Strategies." *Financial Analysts Journal*, vol. 53, no. 2 (March/April): 29–36.

"We find consistent value and momentum return premia across eight diverse markets and asset classes, and a strong common factor structure among their returns. Value and momentum returns correlate more strongly across asset classes than passive exposures to the asset classes, but value and momentum are negatively correlated with each other, both within and across asset classes. Our results indicate the presence of common global risks that we characterize with a three-factor model. Global funding liquidity risk is a partial source of these patterns, which are identifiable only when examining value and momentum jointly across markets. Our findings present a challenge to existing behavioral, institutional, and rational asset pricing theories that largely focus on U.S. equities." (p. 29)

The author's insight here suggests a fusion of technical insight and value investing could yield excess returns.

Asness, Clifford S., Antti Ilmanen, Ronen Israel, and Tobias J. Moskowitz. 2015. "Investing with Style." *Journal of Investment Management*, vol. 13, no. 1 (First Quarter): 27–63.

"Investors are bombarded by a variety of investment strategies from a growing and increasingly complex financial industry, each claiming to improve returns and reduce risk. Amid the clamor, academic research has sifted through the vast landscape and found four intuitive investment strategies that, when applied effectively, have delivered positive long-term returns with low correlation to each other and traditional markets. The four "styles"—value, momentum, carry, and defensive—have uniquely held up across a multitude of asset classes, markets, and time periods using very liquid securities and form the core foundation for explaining the cross-section of returns in most asset classes. The authors discuss the intuition and evidence for these four pervasive styles and detail how to implement a strategy that can access these style premia to improve the risk and returns of traditional portfolios." (p. 27)

Momentum is of most interest to technical analysis in this context.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse H. Pedersen. 2013. "Value and Momentum Everywhere." *Journal of Finance*, vol. 68, no. 3 (June): 929–985.

"Value and momentum ubiquitously generate abnormal returns for individual stocks within several countries, across country equity indices, government bonds, currencies, and commodities. This paper documents the studies of the global returns to value and momentum and explore their common factor structure. The authors conclude that value (momentum) in one asset class is positively correlated with value (momentum) in other asset classes, and value and momentum are negatively correlated within and across asset classes. Liquidity risk is positively related to value and negatively to momentum, and its importance increases over time, particularly following the liquidity crisis of 1998. These patterns emerge from the power of examining value and momentum everywhere simultaneously and are not easily detectable when examining each asset class in isolation." (p. 929)

Because technical analysis often identifies evidence of momentum, the authors' insight in this publication creates a connection suggesting a fusion of technical insight and value investing could be worth investigating.

Chan, Louis K.C., Narasimhan Jegadeesh, and Josef Lakonishok. 1996. "Momentum Strategies." *Journal of Finance*, vol. 51, no. 5 (December): 1681–1731.

"We examine whether the predictability of future returns from past returns is due to the market's underreaction to information, in particular to past earnings news. Past return and past earnings surprise each predict large drifts in future returns after controlling for the other. Market risk, size, and book-to-market effects do not explain the drifts. There is little evidence of subsequent reversals in the returns of stocks with high price and earnings momentum. Security analysts' earnings forecasts also respond sluggishly to past news, especially in the case of stocks with the worst past performance. The results suggest a market that responds only gradually to new information." (p. 1681)

This article suggests that technical analysis may be used to exploit such responses when used in conjunction with observation of changes to fundamental factors.

Dreman, David N., and Michael A. Berry. 1995. "Overreaction, Underreaction, and the Low-P/E Effect." *Financial Analysts Journal*, vol. 51, no. 4 (July/August): 21–30.

"Although earnings surprises have been studied extensively, they have not been examined in the context of contrarian strategies. Positive and negative earnings surprises affect "best" and "worst" stocks in an asymmetric manner that favors worst stocks. Long-term reversion to the mean, in which worst stocks display above-market returns while best stocks show below-market results, regardless of the sign of the surprise, continues for at least 19 quarters following the news. These results are consistent with mispricing prior to the surprise, and a corrective price movement after the surprise is consistent with extant research on underreaction. The mispricing-correction hypothesis explains the superior returns of contrarian strategies noted here and elsewhere in the literature." (p. 21)

These conclusions support the possibility that technical studies could be applied to price data in post-earnings timeframes to identify exploitable market opportunities.

Grundy, Bruce D., and J. Spencer Martin. 2001. "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *Review of Financial Studies*, vol. 14, no. 1 (January): 29–78.

"The voluminous work documenting the apparent abnormal returns to momentum strategies presents a serious challenge to our extant asset pricing models. This paper has documented the statistically significant dynamics of the factor exposure of strategies based on momentum in total returns. Since the factor component makes up one part of a stock's total return, a bet on momentum in total returns is, in part, a bet on momentum in the factors themselves. The mechanics of the strategy place such a bet quite naturally. Those stocks with higher/lower loadings on the factors that performed relatively well during the formation period are more likely to enter the winner/loser portfolio, and the larger the magnitude of the formation period factor realizations, the more likely this event will occur. The sign and the size of the strategy's factor loadings reflect the sign and size of the corresponding factor realizations during the formation period." (p. 29)

The persistence of excess returns from momentum strategies over varying market conditions and time periods strongly supports the notion that technical analysis tools could be used in benchmark-beating methods.

Haleh, H., B. Akbari Moghaddam, and S. Ebrahimijam. 2011. "A New Approach to Forecasting Stock Price with EKF Data Fusion." *International Journal of Trade, Economics and Finance*, vol. 2, no. 2 (April): 109–114.

"Obtaining to the method with the least prediction error is one of the challenging issues of financial and investment markets analyzers. Investors often use two different views of technical and fundamental analysis of prices for buying and selling their desired shares. But each of these two methods alone may have not enough performance due to differences between the actual value of the share and its market price. This paper presents a predictive model named extended Kalman filter which simultaneously fuses information and parameters of technical and fundamental analysis. Then as a real test, the model implemented for the shares of one of industrial company in Iran. Finally, the obtained results will be compared

with other methods results such as regression and neural networks which shows its desirability in short-term predictions." (p. 109)

This paper presents an excellent example of the fusion analysis technique.

Seetharam, Yudhvir, and Christo Auret. 2014. "Fusion Investing: An Innovative Approach to Asset Selection." *Investment Management and Financial Innovations*, vol. 11, no. 1 (April): 157–168.

"This research aims to encapsulate the idea by Lee (2003) and Bird and Casavecchia (2007b) by designing an investment strategy that exploits value, fundamental and momentum anomalies. This fusion strategy has underpinnings in the realm of behavioral finance, namely the value-growth phenomenon and the momentum effect. Using data of all shares listed on the Johanesburg Securities Exchange (JSE) in South Africa, those considered value shares are selected. From that sample, those that are fundamentally sound and exhibit winning momentum characteristics are chosen. Nominal returns of the strategy show promising results as the fusion strategy outperformed both active and passive benchmarks chosen, after costs. The coefficient of variation, a simple measure of variability in the mean return, indicates that an investor seeking higher returns (with higher volatility) would invest in the fusion strategy. On a risk adjusted basis, the results were inconclusive based on the Sharpe and Treynor ratios, but fairly promising based on the Sortino ratio. The Sortino ratio shows that the fusion strategy outperforms all benchmarks chosen, except the Absa Select Equity Fund (known as Fund A). Statistical testing shows that the returns of the strategy are significantly different from zero and follow a non-linear data generating process. Although the screening methods are chosen based on prior studies, no published study has utilized these screens in the sequence outlined above." (p. 157)

Recent Publications Reflecting Evolved Practices in Technical Analysis

Ardila, Diego, Zalan Forro, and Didier Sornette. 2015. "The Acceleration Effect and Gamma Factor in Asset Pricing." Swiss Finance Institute Research Paper No. 15-30 (August).

"We report strong evidence that changes of momentum, i.e. 'acceleration', defined as the first difference of successive returns, provide better performance and higher explanatory power than momentum. The corresponding Γ-factor explains the momentum-sorted portfolios entirely but not the

reverse. Thus, momentum can be considered an imperfect proxy for acceleration, and its success can be attributed to its correlation to the predominant Γ-factor. Γ-strategies based on the 'acceleration' effect are on average profitable and beat momentum-based strategies in two out of three cases, for a large panel of parameterizations. The 'acceleration' effect and the Γ-factor profit from transient non-sustainable accelerating (upward or downward) log-prices associated with positive feedback mechanisms." (p. 1)

Avramov, Doron, Guy Kaplanski, and Haim Levy. 2016. "Talking Numbers: Technical versus Fundamental Recommendations." Working paper (20 July).

"There is an age-old debate between technical and fundamental analyses, the leading schools of thought in economic forecasting. We answer that debate via a comprehensive confrontation of technical and fundamental investment recommendations broadcasted on the TV show "Talking Numbers." In particular, we study 1,599 dual recommendations, where each recommendation contains a fundamental and a technical forecast. The evidence shows that technicians are able to predict abnormal returns in individual stocks up to a twelve-month horizon, while fundamental analysts exhibit weaker predictive ability. Beyond that, neither group is able to predict returns on the market index, equity sectors, bonds, or commodities." (p. 1)

Bilello, Charles V., and Michael A. Gayed. 2014. "An Intermarket Approach to Beta Rotation: The Strategy, Signal, and Power of Utilities." Working paper (31 January).

"It is often said by proponents of the Efficient Market Hypothesis that no strategy can consistently outperform a simple buy and hold investment in broad stock averages over time. However, using a strategy based on the principles of intermarket analysis, we find that this assertion is not entirely accurate. The Utilities sector has many unique characteristics relative to other sectors of the broader stock market, including its higher yield, lower beta, and relative insensitivity to cyclical behavior. Our analysis suggests that rolling outperformance in the sector is not only exploitable, but also provides important signals about market volatility, seasonality, and extreme market movement. We explore historical price behavior and create a simple buy and rotate strategy that is continuously exposed to equities, positioning into either the broad market or the Utilities sector based on lead-lag dynamics. Absolute performance and risk-adjusted returns for this beta rotation approach significantly outperform a buy and hold strategy of the market and of the Utilities sector throughout multiple market cycles." (p. 1)

Dahlberg, C. 2016. "Dow's Theory of Confirmation Modernized." *Optuma* (27 July): www.optuma.com/research.

"Charles Dow was concerned with managing returns in a context of risk. His process required identifying and confirming trends. He was aware that market trends were influenced by economics as well as behavioral biases. Therefore, he required that up and down trends be confirmed in order to be more likely to persist. Dow's Theory of Confirmation created a framework for making investment decisions. This paper takes Dow's concept and applies modern modelling techniques to apply the Theory Confirmation. Test results demonstrate this technique generates superior risk-adjusted returns." (p. 3)

Dyka, A., P. Dudojć, and J. Garus. 2013. "Spectral Analysis of Capital Markets." *Acta Physica Polonica A*, vol. 123, no. 3: 518–521.

"In this paper, the problem of cycles existence in capital markets is addressed. A spectral analysis algorithm, which reduces signal-to-noise ratio is proposed to derive cycle periodograms for the yield function of the DJIA, WIG 20 and NIKKEI 225 indices. Peaks of the periodograms provide premises to postulate the existence of some possible cycles. The 3.5-year periodicity in all 3 indices, which can be related to the Kitchin cycle, is found to be the most distinctive one." (p. 518)

Gayed, Michael A., and Charles V. Bilello. 2016. "Leverage for the Long Run—A Systematic Approach to Managing Risk and Magnifying Returns in Stocks." Working paper (3 March).

"Using leverage to magnify performance is an idea that has enticed investors and traders throughout history. The critical question of when to employ leverage and when to reduce risk, though, is not often addressed. We establish that volatility is the enemy of leverage and that streaks in performance tend to be beneficial to using margin. The conditions under which higher returns would be achieved from using leverage, then, are low volatility environments that are more likely to experience consecutive positive returns. We find that Moving Averages are an effective way to identify such environments in a systematic fashion. When the broad U.S. equity market is above its Moving Average, stocks tend to exhibit lower than average volatility going forward, higher average daily performance, and longer streaks of positive returns. When below its Moving Average, the opposite tends to be true, as volatility often rises, average daily returns are lower, and streaks in positive returns become less frequent. Armed with this finding, we developed a strategy that employs leverage when the market is above its Moving Average and deleverages (moving to Treasury bills) when the market is below its Moving Average. This strategy shows better absolute and risk-adjusted returns than a comparable buy and hold unleveraged strategy as well as a constant leverage strategy. The results are robust to various leverage amounts, Moving Average time periods, and across multiple economic and financial market cycles." (p. 1)

Hasanhodzic, Jasmina, Andrew W. Lo, and Emanuele Viola. 2010. "Is It Real, or Is It Randomized? A Financial Turing Test." Working paper.

"We construct a financial 'Turing test' to determine whether human subjects can differentiate between actual vs. randomized financial returns. The experiment consists of an online video-game where players are challenged to distinguish actual financial market returns from random temporal permutations of those returns. We find overwhelming statistical evidence (p-values no greater than 0.5%) that subjects can consistently distinguish between the two types of time series, thereby refuting the widespread belief that financial markets 'look random'. A key feature of the experiment is that subjects are given immediate feedback regarding the validity of their choices, allowing them to learn and adapt. We suggest that such novel interfaces can harness human capabilities to process and extract information from financial data in ways that computers cannot." (p. 1)

Hestla-Barnhart, Amber. 2015. "Fixing the VIX: An Indicator to Beat Fear." Working paper (13 March).

"Volatility is widely considered to be a category of technical indicators with a simple interpretation - no matter how it is measured volatility is widely believed to rise in a market downturn. This approach is applied to indicators such as the Average True Range (ATR), Bollinger Bands® BandWidth or the most widely followed volatility indicator, VIX, which is formally known as the CBOE Volatility Index®. VIX is widely known as the "Fear Index" because it often increases when the stock market drops and the fear of further price declines increases. While this concept sounds useful, there are significant limitations to executing trading strategies based on VIX and these limitations actually make VIX virtually useless for the average investor. Although it is not widely followed, there is a simple volatility indicator available in the public domain that can be used to implement trading strategies based on the concept of VIX. This indicator, the VIX Fix developed by Larry Williams, overcomes all of the limitations of VIX. This paper will explain that indicator and introduce a quantitative trading strategy to profit from rising fear. The main focus of the paper is on the test results." (p. 1)

Munenzon, Mikhail. 2015. "Evaluation of Systematic Trading Programs." *Journal of Trading*, vol. 10, no. 1 (Winter): 37–55.

"This paper is intended as a non-technical overview of the issues I found valuable in evaluation of systematic trading programs both as a systematic trader and as a large, institutional investor, having looked at numerous, diverse managers in this space on a global basis over the years. Some of the topics discussed below apply to discretionary traders and all types of investment organizations though the focus will always remain on systematic trading. Throughout this paper, I assume that systematic trading refers to an investment program for exchange listed instruments or spot FX that generates signals, manages positions and executes applicable orders via an automated, previously programmed process with little or no human interference. The list of topics is not by any means exhaustive but it should be sufficient to allow an investor to start on the path towards successful allocations with systematic trading managers. As I hope will become clear over the course of this paper, systematic trading is a highly unique field with its own set of advantages over other investment approaches that investors should not overlook." (p. 37)

Northington, K., and C. Dahlberg. 2016. "Volatility Based Support and Resistance." *Optuma*: www.optuma.com/research.

"Favorable risk adjusted returns can be, at times, as difficult to attain as a porcupine in a balloon factory. Forces are constantly at work to ensure that neither of these occur. What follows will outline an emerging solution for forecasting technical price and volatility value levels. The solution is termed Volatility-Based Support Resistance (VBSR). This paper explains how VBSR enables risk analysts, portfolio managers, and trading execution teams to more accurately forecast best price levels for accumulation. Additionally, light will be shed on identifying points where market implied volatility can be forecasted to alter its prevailing directional track. Proper risk governance & oversight mandates that we execute careful processes for selecting opportunities. Steps to include macro market influences, investment mandates, and price/value forecasting involve multiple groups in the decision framework. Processes consume time, and cause opportunities to be missed. Time, not unlike confirmation, consumes Alpha." (p. 2)

Pätäri, Eero, Pasi Luukka, Elena Fedorova, and Tatiana Garanina. 2016. "The Anatomy of Returns from Moving Average Trading Rules in the Russian Stock Market." *Applied Economics Letters* (June).

"This paper examines the profitability of index trading strategies that are based on dual moving average crossover (DMAC) rules in the Russian stock market over the 2003–2012 period. It contributes to the existing technical analysis (TA) literature by comparing for the first time in emerging markets the relative performance of individual stocks' trading portfolios with that of trading strategies for the index that consists of the same stocks (i.e., the most liquid stocks of the Moscow Exchange). The results show that the best trading strategies of the in-sample period can outperform buy-and-hold strategy during the subsequent out-of-sample period, although with low statistical significance. In addition, we document the benefits of using DMAC combinations that are much longer than those employed in previous TA literature. Moreover, the decomposition of the full-sample-period performance into separate bull- and bear-period performances shows that the outperformance of the best past index trading strategies over is mostly attributable to the fact that they managed to stay mostly out of the stock market during a dramatic crash caused by the global financial crisis." (p. 1)

Sornette, Didier, Anders Johansen, and Jean-Philippe Bouchaud. 1996. "Stock Market Crashes, Precursors and Replicas." *Journal de Physique. I*, vol. 6, no. 1 (January): 167–175.

"We present an analysis of the time behavior of the S&P500 (Standard and Poor's) New York stock exchange index before and after the October 1987 market crash and identify precursory patterns as well as aftershock signatures and characteristic oscillations of relaxation. Combined, they all suggest a picture of a kind of dynamical critical point, with characteristic log-periodic signatures, similar to what has been found recently for earthquakes. These observations are confirmed on other smaller crashes, and strengthen the view of the stock market as an example of a self-organizing cooperative system." (p. 167)

Zakamulin, Valeriy. 2014a. "Dynamic Asset Allocation Strategies Based on Unexpected Volatility." *Journal of Alternative Investments*, vol. 16, no. 4 (Spring): 37–50.

"In this paper we document that at the aggregate stock market level the unexpected volatility is negatively related to expected future returns and positively related to future volatility. We demonstrate how the predictive

ability of unexpected volatility can be utilized in dynamic asset allocation strategies that deliver a substantial improvement in risk-adjusted performance as compared to traditional buy-and-hold strategies. In addition, we demonstrate that active strategies based on unexpected volatility outperform the popular active strategy with volatility target mechanism and have the edge over the widely reputed market timing strategy with 10-month simple moving average rule." (p. 37)

Zakamulin, Valeriy. 2014b. "The Real-Life Performance of Market Timing with Moving Average and Time-Series Momentum Rules." *Journal of Asset Management*, vol. 15, no. 4 (August): 261–278.

"In this paper, we revisit the myths regarding the superior performance of market timing strategies based on moving average and time-series momentum rules. These active timing strategies are very appealing to investors because of their extraordinary simplicity and because they promise substantial advantages over their passive counterparts (see, for example, the paper by M. Faber (2007) 'A Quantitative Approach to Tactical Asset Allocation' published in the Journal of Wealth Management). However, the 'too good to be true' reported performance of these market timing rules raises a legitimate concern as to whether this performance is realistic and whether investors can expect that future performance will be the same as the documented historical performance. We argue that the reported performance of market timing strategies usually contains a considerable data-mining bias and ignores important market frictions. To address these issues, we perform out-of-sample tests of these two timing models in which we account for realistic transaction costs. Our findings reveal that the performance of market timing strategies is highly overstated, to say the least." (p. 261)

Not all studies agree that technical analysis methods increase value.

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