

## CHAPTER 6

### Technical Analysis Demystified

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#### The ‘New’ New Finance

New Finance is a euphemism for behavioral finance, an approach based primarily on theoretical results aimed at explaining empirical anomalies in security prices. Following Kahneman and Tversky (1979), these theories are derived from psychological biases that appear in human behavior. Consistent with the positivist approach, logical explanations are provided for empirical results that are inconsistent with the efficient markets hypothesis (EMH). While recognizing that there are anomalies in prices, New Finance is not too concerned with demonstrating that observed anomalies can be used to generate abnormal returns. This is the preserve of the ‘New’ New Finance. The progress of this ‘movement’ has been remarkable, encompassing even the key publication outlets of modern Finance, e.g., Zhu and Zhou (2009). The research agenda is outlined in Friesen et al. (2009): “At present, we lack theoretical models that can explain the presence of pattern-based trading rules, though several empirical studies suggest that such rules may be profitable.” Is it possible that the last vestige of the EMH — weak form efficiency — is falling?

## 6.1 What is Technical Analysis?

### 6.1.1 *Different Forms of Technical Analysis*

Much like ‘fundamental analysis’, ‘technical analysis’ suffers from an oversimplified interpretation given to this body of techniques. For many years, adherents of modern Finance maintained the empirical evidence against technical analysis was overwhelming. For example, Malkiel (1990, p. 133) claims:

Technical rules have been tested exhaustively by using stock price data on both major exchanges, going back as far as the beginning of the 20th century. The results reveal conclusively that past movements in stock prices cannot be used to foretell future movements. The stock market has no memory. The central proposition of charting is absolutely false, and investors who follow its precepts will accomplish nothing but increasing substantially the brokerage charges they pay.

Yet, in a remarkable about-face, this *‘overwhelming’ evidence has been contradicted* and the prevailing academic view now seems to be: “Most recent studies investigating return predictability have concluded that security returns are predictable from information that investors can easily obtain” (Beller *et al.* 1998). It is not difficult to find similar views, e.g., Brock *et al.* (1992), Lo and MacKinlay (1999), Siegel (1998, ch. 17), and Savin *et al.* (2007). Despite this accumulating evidence, some modern Finance stalwarts still maintain that *consistently* profitable trading rules have not yet been demonstrated and the results are likely due to ‘data snooping’ and the like, e.g., Bessembinder and Chan (1998), Sullivan *et al.* (1999) and Ready (2002).<sup>1</sup>

Much like fundamental analysis, technical analysis is an important, diverse and sometimes complicated approach to the evaluation of both equity securities and commodity derivatives that has been overly simplified in traditional tests of the ‘weak form’ efficient markets hypothesis. The methods and procedures involved in taking a body of ‘technical information’ and translating that information into an evaluation of whether a stock

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<sup>1</sup>The production of empirical results on technical analysis in modern Finance provides an interesting illustration of McCloskey’s ‘conversations among academics’. For example, a recent listing of eighteen studies, largely from the core journals of modern Finance, that provide either direct or indirect empirical support for technical analysis can be found in Lo *et al.* (2000, p. 1706). This list does not include the numerous studies outside the core journals of modern Finance, i.e., outside the conversation among strong adherents of modern Finance, that also provide support for technical analysis.

is correctly valued does not necessarily correspond to conventional methods of testing whether, on average, changes in a particular type of technical information is rapidly translated into prices. The perception that technical analysis is an alternative and competitive approach to fundamental analysis is also inaccurate. ***Much of technical analysis is concerned with market timing and speculative trading***, not with investment based on the long term prospective yield of the security. Certain types of technical analysis may be used in conjunction with fundamental analysis, e.g., as a guide to market timing for determining when to purchase securities that have been identified using fundamental analysis. Some forms of technical analysis can be theoretically rationalized in terms of fundamentals, such as the intra-day interaction between market liquidity and order flow. Even the precise dividing line between technical and fundamental analysis is unclear, with some 'technical' trading rules exploiting information that would best be characterized as fundamental.

The boundaries of technical analysis can be defined with reference to the type of information that is being used in the specific trading rule or valuation model. More precisely, ***technical analysis involves the use of 'market generated data'*** as inputs. This includes: current and past security prices; aggregations of these prices into market and sector indexes; total volume; up/down volume and ratios or differences for the number advancing issues to number of declining issues (e.g., the advance/decline line); implied volatilities for put and call options; relationships among bond yields, such as the 'confidence index' published by *Barron's*; odd lot trading volume; and short sales positions in aggregate or by type of trader (specialist vs. odd lot). It is possible to extend the set of information to include other more circumspect types of 'market generated' data, e.g.: mutual fund cash positions; credit and debit balances with brokerage firms; insider trading transactions (revealed through SEC filings such as Form 4); and, investment advisory opinions. Technical analysis involves the processing of these sources of information into valuation or market timing decisions about securities. In some cases the processing is cursory, in other cases the processing is quite sophisticated.

Technical analysts are often referred to as 'chartists', e.g., Siegel (1998, p. 240), Lo *et al.* (2000, p. 1705). Though many types of technical analysis employ charts, this reference confuses the method of analysis with the type of information being analyzed and the type of signal that is expected. Though widely used by technical analysts, ***charts are neither necessary or sufficient for technical analysis***. Even when charts are being

used, there are a range of possible techniques that can be employed. For the same set of data, different charting techniques may produce different trading signals. Some types of charting techniques are aimed at specific sampling intervals, e.g., point-and-figure charts are often used to analyze intra-day price movements while moving average charts are applied to, say, time series of daily or monthly prices. Ultimately, charts are only visual aides. It is always possible to translate the information in a chart to mathematical or statistical expressions, though this may be difficult to accomplish in many cases, e.g., Treynor and Ferguson (1985). It is unfortunate that by stressing the connection of technical analysis with charting the theoretical foundation for the general approach is overlooked. Taken as a whole, technical analysis is much more than an atheoretical reading of the ‘tea leaves’.

Technical analysis is a vast subject containing so many contributions that it is not possible in this chapter to provide more than a brief overview. Such an overview has to deal with selecting topics for examination. ***The subject has not been static.*** For example, classic texts, such as Edwards and Magee (1966), do not deal with numerous concepts such as oscillators and stochastics that have risen to popularity since the early 1970s and now form the grist of various on-line sites featuring technical indicators. In addition, significant contributions to the subject span both the commodity and securities markets. Initially, key contributions to technical analysis, such as the Dow theory, were concerned with stock markets. Over time, the emphasis on speculative trading of derivative securities in commodity markets resulted in many essential sources on technical analysis, e.g., Kaufman (1978), being concerned with trading in commodity derivative markets. In turn, the rapid development of day trading in stocks, enhanced execution ability, and the dramatic drop in transactions costs associated with on-line trading and the growth of ETNs has created a resurgence of contributions concerned with stocks, e.g., Elder (1993) and Blau (1995). Those interested in the current state of theory are advised to examine a number of the excellent websites featuring the ‘technical’ approach, e.g., [www.marketscreen.com](http://www.marketscreen.com), [www.futuresource.com](http://www.futuresource.com) or [clearstation.etrade.com](http://clearstation.etrade.com).

### 6.1.2 *Conceptual Foundations of Technical Analysis*

#### *Astrological Beginnings*

Technical analysis is based on an investment philosophy which does not believe in the efficient markets hypothesis. Where the strong believers in



EMH have an intellectually appealing conceptual foundation based on a unifying theoretical framework, there is *a buffet of competing theories* that provide the conceptual foundation for technical analysis. Certain technical theories have mathematical roots that stretch back centuries, such as the Fibonacci numbers used in the Elliott wave theory. Ehrenberg (1928) relates what is perhaps the earliest known application of technical analysis on the Antwerp exchange during the 16th century where the emergence of liquid financial and commodity markets created the potential for significant gains or losses from speculation, e.g., Poitras (2009). It was difficult for merchants actively involved in the bill or commodity markets to avoid the implications of rapid price changes on the exchange: “dealing in commodities in Antwerp [was] a risky business for anyone not able to follow the market from hour to hour and even for those who did so” (Ehrenberg 1928, p. 240). The pressing need for merchants to predict price movements created the preconditions for the emergence around 1540 of an interesting early version of technical analysis based on astrology (Ehrenberg 1928, pp. 240–242).

The originator of this security market forecasting system was one Christopher Kurz, an astrologer from Nuremberg. The Tuchers, among the most prominent merchant families of that time, were his most important clients. According to Ehrenberg (p. 240), around this time:

astrological prognostications flourished in the Netherlands; there were prophecies of every kind which were reproduced in print. Christopher Kurz had puzzled out an astrological system by which he could foretell prices. He praised his invention to the Tuchers, mixing sober business statements with fantastic combinations in a way that seems absurd to use, but which probably at the time gave quite a different impression . . . Lienhard Tucher made marginal notes on the reports that Kurz sent which prove that he read them carefully and did not fail to observe the prognostications.

Acknowledging that ‘trade in spices needs great foresight’, Kurz claims to have a system for forecasting the prices of pepper, ginger and saffron a fortnight ahead. To quote from one of Kurz’s reports to Tucher (quoted in Ehrenberg 1928):

I sought it three years but until this year found it not. I think God hath given it to me. I have observed it for the space of a year. Yet I will not boast myself of it, till I myself have observed it for yet a time longer with mine own eyes and have traced it out. Yet I doubt not, it is well founded . . . In the same manner I have known how to show for the matter as touching cinnamon, nutmegs and cloves . . . likewise with bills can one

happen on many a good chance. As ye have often noted in my writings to you how great an alteration is there here day by day in bills on Germany, Venice, or Lyons, so that in the space of eight, ten, fourteen or twenty days with other folks' money, a man may make a profit of 1, 2, 3, 4, 5, or more per cent., with such there is here each day great business on the Bourse. On these also have I my experiment so that I may foretell not only from week to week the Strettezza and Largezza (tightness or ease in money), but also for each day and whether it shall be before midday. I have, however, nigh forgot this again, since I have found you so reluctant.

The similarities of Kurz's claims with those often advanced by modern technical analysts are striking.

Though there has been some progress towards precision in specifying trading rules associated with New Finance theories, modern technical analysis has generally been characterized by vagueness in making precise statements about how specific technical trading rules generate future price predictions. For example, concepts such as 'support and resistance levels' are used even though competing technical analysts often identify different support and resistance levels when confronted with the same data. Similar observations can be made about chart patterns, such as 'head-and-shoulders' and 'W-bottoms'. Technical analysts have little *ex post* difficulty identifying such patterns successfully in charts for past price data but exhibit *considerable ex ante disagreement* when asked to identify such patterns to use in predicting future price behaviour. There is a widespread tendency for traditional technical analysts to claim a special ability in interpreting available data which is, somehow, intuitive enough to be incapable of precise formulation.

The correspondence between Kurz's astrological system and modern technical analysis can be captured by examining the four point conceptual scheme of Levy (1966) adopted in Francis (1983, p. 434) which provides a rough characterization of the '*basic assumptions of [traditional] technical analysis*':

1. Market value is determined solely by the interaction of supply and demand.
2. Supply and demand are determined by numerous factors. These factors can be both rational and irrational. Included in these factors are those of importance to fundamental analysts, as well as moods, sentiment, guesses and blind faith. The market is a mechanism for weighing each of these factors on a continuing basis.

3. Though there are minor fluctuations in the market, ***stock prices have a tendency to move in trends that persist for appreciable lengths of time.***
4. Changes in trend are the result of shifts in supply and demand. These shifts, no matter what factors determine the shift, can be detected sooner or later in analysis of market action and used to forecast future price movements.

Interpreting ‘chart patterns’ to be ‘astrological chart patterns’ reveals an interesting, if somewhat whimsical, connection between Kurz’s 16th century astrological system for predicting future security price movements and the methods used in modern technical analysis. It also provides a foundation for a classification of technical methods into three general groups: traditional technical analysis, based on chart formations and moving average methods; New Finance, based on generalizing modern Finance to incorporate pricing anomalies using psychological predictions about investor behavior; and, mystical finance encompassing a range of technical theories, from the universal to the ephemeral, that cannot be justified by traditional or New Finance methods, e.g., the Elliott wave theory.

### *Keynes, New Finance, and the EMH*

As evidenced by Akerlof and Shiller (2009, esp. ch. 11), it is gradually being recognized that the connection between the EMH and New Finance explanations of technical trading can be traced back to Keynes, especially Chapt. 12 of the *General Theory*. ***For Keynes, the EMH is a convention.*** This is an important observation because in the Keynesian model, “conventions are essentially shared rules of behavior that enable individuals to take actions in situations where the future results of these actions are unknowable . . . though the future may be unknowable the existence of conventions and the belief that they will be maintained provide a basis for decision making under uncertainty” (McKenna and Zannoni 1993, pp. 402, 403).<sup>2</sup> The weakness of the EMH as a convention is that the actual security

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<sup>2</sup>While it is tempting to extend the discussion to notions of individual liberty and freedom, this would take the discussion too far afield. However, it is worth observing at this point that this concept of uncertainty “requires a social matrix for its existence” (McKenna and Zannoni 1993, p. 405). This is almost diametrically opposed to the neo-classical approach, of which the modern portfolio theory is an extension. In this approach, decisions are absolute and social conventions and institutions are not required to situate the optimal solution, which is conceived to be immutable.

prices are not being determined with reference to the long-term prospective yield. Rather prices are being determined “as the outcome of a large number of ignorant individuals” and misguided professional investors and speculators. This produces a stock market that, when confidence in the convention is ‘less plausible than usual’, is “subject to waves of optimistic and pessimistic sentiment, which are unreasoning and yet in a sense legitimate, where no solid basis exists for a reasonable calculation” (p. 154). Such fluctuations are so pervasive that “the energies and skill of the professional investor and speculator are mainly occupied... not with making superior long-term forecasts of the probable yield of an investment over its whole life, but with foreseeing changes in the conventional basis of valuation a short time ahead of the general public” (p. 154).

This reference to convention has deep philosophical implications that cannot be ignored. *Conventions are the result of social interaction*, what McKenna and Zannoni (1993) pedantically refer to as the social matrix (the cultural context within which individuals exercise their freedom). As a consequence of the EMH being a convention, the extent of the violent fluctuations in the market depend on the temporal state of the social matrix. In other words, the institutional, social and historical context will impact the security pricing process. The same event occurring at different times may produce a violent fluctuation in pricing in one period and have no impact at another time. Uncertainty is created by the infinite number of future outcomes which are possible at a given point in time. The specific outcome which occurs “is the result of individual choice in the context of social interaction... It is not the case that the far distant future is sometimes more knowable than at other times. It is always simply unknowable. What does change... is the meaning people choose to attach to this fact, and hence the manner in which people’s behavior responds to this uncertainty” McKenna and Zannoni (1993, p. 403).

It is evident from his personal and professional investment practices that Keynes is not among the full fledged dis-believers in the EMH and, as a result, can not be considered in the same camp as the technical analysts. Yet, there is substantive misgivings about the success of fundamental analysis: “Investment based on genuine long-term expectation is so difficult today as to be scarcely practicable. [An investor] who attempts it must surely lead much more laborious days and run greater risks than [an investor] who tries to guess better than the crowd how the crowd will behave; and given equal intelligence, he may make more disastrous mistakes ... It needs *more* intelligence to defeat the forces of time and our ignorance of the future than

to beat the gun” (p. 157). Besides, there is more excitement in the chase after speculative profit: “... life is not long enough; – human nature desires quick results, there is a peculiar zest in making money quickly, and remoter gains are discounted by the average man at a very high rate” (p. 157).

The reliance on the social matrix is one element of the Keynesian approach that is worrisome to neo-classical economists and, in the present context, presumably also to modern portfolio theorists. Yet, to be relevant to present day security markets, this material has to be reworked to fit the contemporary social matrix. Conventions, which are so important for decision making under uncertainty, depend fundamentally on the social matrix. In this vein, Keynes was writing at a time that was different in many ways from the world of today. There has certainly been substantive changes in financial markets since the time of the *General Theory*. Perhaps the world has changed enough that the investor motivated by long-term expectations has come to predominate, inducing an EMH convention which is more stable and less susceptible to violent fluctuation? Putting aside for the moment the empirical evidence to the contrary provided by the high tech/dot com/NASDAQ 5000 stock bubble of 2000 or the slow motion global crash of 2008–2009, what suggestions would Keynes have for those seeking to employ a security valuation strategy based on fundamental analysis?

It is difficult to deny that the ‘zest’ for quick profit is any less vigorous today than in times gone by. It is also still the case that (p. 157): “The game of professional investment is intolerably boring and overexacting to anyone who is entirely exempt from the gambling instinct”. The investor who would seek to engage in fundamental analysis, i.e., “an investor who proposes to ignore near-term market fluctuations” and purchase a security on the basis of long-term prospective yield, is advised of the need for ‘greater resources for safety’ and not to “operate on so large a scale, if at all, with borrowed money”. All these potential difficulties are compounded by the following prediction (p. 158): “If I may be allowed to appropriate the term *speculation* for the activity of forecasting the psychology of the market, and the term *enterprise* for the activity of forecasting the prospective yield on assets over their whole life, it is by no means always the case that speculation predominates over enterprise”. Unfortunately, this hopeful statement is followed by: “As the organization of investment markets improves, the risk of predominance of speculation does, however, increase”. If this prediction is correct, fundamental analysis is likely to be even more difficult today than at the time of the *General Theory*.

### *Old Finance and Technical Analysis*

The current debate over the merits of technical analysis can be traced back to the beginnings of modern Finance in the late 1950s and early 1960s. Prior to this time, the potential benefits of technical analysis were generally acknowledged by many practitioners, though the subject was largely disparaged by adherents of ‘old finance’ due to the emphasis on speculative trading strategies.<sup>3</sup> Technical analysis, in some form or other, has been practiced in European securities market at least since the 16th century (Poitras 2000). Nison (1996) finds evidence for the use of candlestick chart technical analysis in 18th century Japanese commodity markets. Brock *et al.* (1992, p.1731) observe: “In the United States, the use of trading rules to detect patterns in stock prices is probably as old as the stock market itself”. Prior to the widespread availability of detailed and accurate financial statement information about publicly traded companies, market generated data were often the most important source of information about a security. The introduction of the NYSE stock ticker in 1867 marks the beginning of an important technological advance that brought ‘tape reading’ into the lexicon of mainstream society. Prior to this time, the barriers to information transmission made the analysis of market generated data largely the preserve of those able to directly observe trading at the exchange.<sup>4</sup>

Though a definitive intellectual history of technical analysis is yet to be written, the origin of traditional technical analysis is usually traced to the late nineteenth century when Charles Dow originated the Dow–Jones Industrial Index.<sup>5</sup> Together with his successor at the *Wall Street Journal*, William Peter Hamilton, Dow was an active promoter of technical analysis

<sup>3</sup>Wyckoff (1933, p. 105) quotes a newspaper reporter from the 1920s bemoaning ‘unwarranted market declines’ caused ‘by purely mechanical interpretation of a meaningless set of lines’ on ‘charts of professional stock traders’.

<sup>4</sup>A similar revolution happened in the last decade of the 20th century with the impact of computing and telecommunications technology on global securities trading. The substantive impact of these technological factors on the programmed trading driven market crash of October 1987 marks a symbolic beginning to this revolution. The inability of regulators to deal with events such as the emergence of global ETN’s and the growth of the OTC derivatives market can be traced to a regulatory failure to anticipate the implications of the fundamental technological changes impacting securities markets.

<sup>5</sup>There are a number of sources that do pay some attention to the history. For example, Kaufman (1978, chs. 12, 13) provides considerable background on the important, if unrecognized, individuals in the history of technical analysis such as: R.N. Elliot, developer of the ‘Elliot Wave Principle’ based on Fibonacci numbers, during the mid-1930s; the various systems developed by William Gann, starting in the mid-1930s and continuing until the 1950s; William Dunnigan, originator of ‘the thrust method’, during the

based on market averages. These developments by Dow and Hamilton were not produced in isolation. As evidenced in Wyckoff (1910), other notions commonly used in modern chart reading, such as resistance and support levels, were in use around that time. Graham and Dodd (1934, p. 608) recognize that ‘technical study’ had “increased immensely during the past ten years. Whereas security analysis suffered a distinct and continued loss of prestige beginning about 1927, chart reading apparently increased the number of its followers even during the long depression”. These followers of chart reading were to be found in significant numbers in Wall Street. Graham and Dodd identify a number of references for these techniques including: Gartley (1934), which provides a development of moving average techniques examined in Gartley (1930); Schabacker (1930), which Kaufman (1978) describes as outstanding and a ‘must read’; and Rhea (1932) which is still an essential source for examining the Dow theory.

Graham and Dodd (1934) and later editions up to and including Graham *et al.* (1962) took a dim view of ‘market analysis’ which included technical analysis as a significant subset. A number of logical arguments were advanced against this approach. Though the connection was not recognized, the Graham and Dodd position against technical analysis was supported by statistical evidence, which started to accumulate during the 1950s, that security price changes were serially uncorrelated.<sup>6</sup> These statistical studies were broadly interpreted as being strong evidence against technical analysis. Though some adherents of modern Finance have recently claimed that this interpretation of the evidence was incorrect (e.g., Lo *et al.* 2000; Jegadeesh and Titman 2001), at the time enthusiasm for the evolving efficient markets paradigm of modern Finance outweighed the answers to the common sense question: if technical analysis is incapable of generating abnormal returns, why are so many technical analysts employed by the securities industry?<sup>7</sup>

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early 1950s; Eugene Nofri, originator of the ‘congestion-phase system’; Chester Keltner, originator of the ‘minor trend rule’, during the late 1950s.

<sup>6</sup>The statistical attack on technical analysis by academics can, arguably, be traced back to Cowles (1934) where the performance of the Hamilton version of the Dow theory is examined. Cowles found that returns from the Dow theory lagged the market which is inconsistent with the claim that the Dow theory can be used for market timing. Brown *et al.* (1998) reconsider Cowles’ results and observe: “Cowles compares the returns obtained from Hamilton’s market timing strategy to a benchmark of a fully invested stock portfolio. In fact, the Hamilton portfolio, as Cowles interprets it, is frequently out of the market. Adjustment for systematic risk appears to vindicate Hamilton as a market timer”.

<sup>7</sup>While there are a significant number of technical analysts on Wall Street, the preponderance of analysts are of the fundamental persuasion.

In the process of making a headlong rush to judgment, modern Finance was quick to dismiss conceptual arguments supporting the foundations of technical analysis.

Levy (1966) and Francis (1983) are not the only statements of the conceptual framework for traditional technical analysis. Following Murphy (1999), the framework can be reduced to three propositions: *market movements discount all relevant information; prices move in trends*; and, *history repeats itself*.<sup>8</sup> Though reference is made to ‘all relevant information’ being incorporated into prices, hiding in the background is a view of equity security pricing that is decidedly contrary to the view contained in the Graham and Dodd approach. For example, Edwards and Magee (1966, p. 5) observe:

It is futile to assign an intrinsic value to a stock certificate. One share of United States Steel, for example, was worth \$261 in the early fall of 1929, but you could buy it for only \$22 in June 1932. By March 1937, it was selling for \$126 and just one year later for \$38 . . . This sort of thing, this wide divergence between presumed value and actual value, is not the exception; it is the rule; it is going on all the time. The fact is that the real value of a share of United States Steel common is determined at any given time solely, definitely and inexorably by supply and demand which are accurately reflected in the transactions consummated on the floor of the New York Stock Exchange.

Though not as sophisticated as the model of stock pricing proposed by Keynes (e.g., Poitras 2002a), technical analysts recognize that both rational and irrational factors can impact market prices. The resulting trading strategies are generally consistent with the ‘anticipation approach’, as opposed to the ‘intrinsic value’ approach, to security valuation.

For Graham and Dodd (1934, p. 608), technical analysis is part of the more general subject of ‘market analysis’ that seeks to predict the ‘short-term behavior of the stock market’, as opposed to the ‘long-term market considerations’ that are the basis of the intrinsic value approach. Two approaches to market analysis are identified. One approach uses ‘all sorts of economic factors’, including general and specific business conditions, short-term interest rates, political considerations and so on. The other approach “finds the material for its predictions exclusively in the

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<sup>8</sup>Kaufman (1978, p. 192) provides the following quote from R.N. Elliot, originator of the Elliot wave theory, that describes the epistemological approach of technical analysis: “Even though we may not understand the cause underlying a particular phenomenon, we can, by observation, predict the phenomenon’s recurrence”.



past action of the stock market”, i.e., technical analysis. “The underlying theory of [this] approach may be summed up in the declaration that ‘the market is its own best forecaster’”. While it is always theoretically possible to reconstruct chart analysis in terms of mathematical or statistical equations, this will typically be difficult to do without the aid of computing power. Writing prior to the widespread introduction of mainframe computers, Graham and Dodd observe that technical analysts “generally studied [the behavior of the market] by means of charts on which are plotted the movements of individual stocks or of ‘averages’”. As consequence, Graham and Dodd refer to technical analysis as ‘chart reading’ and to technical analysts as ‘chartists’. Though not fully descriptive, this terminology has carried forward into the modern lexicon.

### *The Feedback Effect*

The arguments advanced by Graham and Dodd (1934, p. 609) against technical analysis are

1. Chart reading cannot possibly be a science.
2. It has not proved itself in the past to be a dependable method of making profits in the stock market, at least not one available to the general public.
3. Its theoretical basis rests on faulty logic and also upon mere assertion.
4. Its vogue is due to certain advantages it possesses over haphazard speculation, but these advantages tend to diminish as the number of chart students increases.

These arguments are carried verbatim into later editions. The intuition underlying each of these points is presented. All four points revolve around an observation that can be characterized as the ‘*feedback problem*’. This problem is illustrated in a discussion of the first point:

If [technical analysis] were a science, its conclusions would be as a rule dependable. In that case, everybody could predict tomorrow’s or next week’s price changes, and hence every one could make money continuously by buying and selling at the right time. That is patently impossible. A moment’s thought will show that there can be no such thing as a scientific prediction of economic events under human control. The very “dependability” of such a prediction will cause human actions which will invalidate it. Hence thoughtful [technical analysts] admit that continued success is dependent upon keeping the successful method known only to a few people.

There are two key observations being made here. One observation deals with the inherent unpredictability of events under human control. This is the essence of the epistemological problem confronting the human sciences. The other point has to do with the need to keep successful technical analysis systems secret in order to prevent a ‘feedback problem’ where trading on a successful system by large numbers of traders eliminates the profitability.<sup>9</sup> But if successful systems are secret, how can such systems be tested to assess *ex ante* profitability?

Graham and Dodd recognize that security analysis is not immune to the inherent unpredictability of events under human control. Yet, there are differences (GDC, p. 714):

The past earnings of a company supply a useful indication of its future earnings — useful, but not *infallible*. Security analysis and [technical] analysis are alike, therefore, in the fact that they deal with past data that are not conclusive as to the future. However, we are inclined to the view that for the typical analyst the so-called “fundamental” information for investment-quality shares — sales, earnings, asset and capital data, etc. — lends itself to more meaningful interpretation than does [technical] information. Moreover . . . there is the added difference that the security analyst can protect himself by a *margin of safety* that is denied to the [technical] analyst.

This emphasis on the margin of safety is not the only difference. The longer time horizon of fundamental analysis looks beyond the near-term horizon that is reflected in the ‘consensus’ forecast embedded in current stock prices generated by “the analysis and advice supplied in the financial district [that] rests upon the near-term business prospects of the company considered”. In GDC, there is explicit recognition of the possibility that the feedback problem could also affect the intrinsic value approach. However, compared to the longer-term buy-and-hold intrinsic value approach, the reliance of technical analysis on near-term trading intensive techniques means that “the expense of trading weights the dice heavily” against this approach.

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<sup>9</sup>Practicing technical analysts are well-aware of the feedback problem. Consider the following statement from the Dow theorist, Richard Russell (Du Bois 2000): “I began publishing the Primary Trend Index (PTI) in 1971. It’s a compilation of eight components that measure only market action. There’s no subjective interpretation involved. I prefer not to name the components. If everybody followed the same ones in the same way, the PTI would lose its usefulness”.

In addition to the logical objections presented by the feedback problem, Graham and Dodd observe that there is nothing in the structure of technical analysis that ensures adequate performance (GDC, pp. 714, 715):

You may learn a great deal about the technical position of individual stocks by studying charts of their past market performance, but the question is whether you learn enough to predict the future with sufficient accuracy to operate profitably over time in the stock market. In other words, does the information which you derive from the past market action of individual issues prove valuable *often enough* for you to invest profitably in common stocks?

The Levy (1966) and Francis (1983) four point conceptual foundation for technical analysis could be accepted without any assurance that sustainable and profitable strategies could be identified and pursued. While there may be certain situations where technical analysis provides ‘really convincing cases’, such cases are not the norm: “such precise signals apparently occur at wide intervals, and all too often the chart configurations are such that chart readers ‘find themselves adrift on a sea of ambiguities’”.

The Graham and Dodd (1934, p. 615) objections to technical analysis extend to all forms of market analysis that seek to profit from making near-term predictions of common stocks:

We are skeptical of the ability of the analyst to forecast with a fair degree of success the market behavior of individual issues over the near-term future — whether he bases his predictions upon the technical position of the market or upon the general outlook for business or upon the specific outlook for individual companies.

Despite arguing for the absence of a scientific approach to such market analysis, Graham and Dodd were not able to shake the observation that such activities are widely used in the investment industry. This perception increased from edition to edition reaching the conclusion (GDC, p. 716):

The more intelligent chart students recognize these theoretical weaknesses, we believe, and take the view that market forecasting is an *art* that requires talent, judgment, intuition, and other personal qualities. They admit that no rules of procedure can be laid down, the automatic following of which will ensure success. Hence the widespread tendency in Wall Street circles toward a composite or eclectic approach, in which a very thorough study of the market’s performance is projected against the general economic background and the whole is subjected to the appraisal of experienced judgment.

While recognizing that the prevalence of market analysis in Wall Street circles implicitly supported the possibility of profitably pursuing such an approach, Graham and Dodd still left no room for the possibility of a systematic, quasi-scientific technical analysis.

### 6.1.3 *New Finance and Mystical Finance*

#### *Revival of Technical Analysis?*

In recent years, modern Finance has revisited the possibility that there may be something in technical analysis beyond being a convenient punching bag for the efficient markets hypothesis. Consistent with the economic positivism that drives this approach, the process of ‘empirical verification’ has guided this change. For example: “statistically significant evidence has been presented from momentum profits” (Chan *et al.* 2000); “a systematic and automatic approach to technical pattern recognition using nonparametric kernel regression . . . provide[s] incremental information and may have some practical value” (Lo *et al.* 2000); “trading strategies that buy past winners and sell past losers realize significant abnormal returns . . . relative strength profits cannot be attributed to lead-lag effects that result from delayed stock price reactions to common factors” (Jegadeesh and Titman 1993); “momentum profits have continued in the 1990s, suggesting that the . . . results were not the product of data snooping bias” (Jegadeesh and Titman 2001); “Hamilton’s [Dow theory] timing strategies actually yield high Sharpe ratios and positive alphas for the period 1902–1929 . . . Neural net modeling to replicate Hamilton’s calls provides interesting insight into the Dow Theory” (Brown *et al.* 1998). This change of location for the boundaries of modern Finance requires some reworking in the classification of ‘technical analysis’ theories.

In modern Finance, evidence in favor of certain types of technical analysis has been accompanied by a range of other statistical studies that have questioned the empirical validity of the efficient markets hypothesis. The scope of these studies includes evidence for: pricing anomalies, such as the January effect and the small firm effect, e.g., Dimson *et al.* (2002); serial correlation in returns, e.g., Campbell *et al.* (1997) and Lo and Mackinlay (1999); value stocks outperforming growth stocks, e.g., Fama and French (1998); and, various aspects of behavioral finance such as a bias to buying winners and selling losers, e.g., Shefrin and Statman (1984); De Bondt

and Thaler (1985, 1987), Shefrin (2000), and Akerlof and Shiller (2009).<sup>10</sup> Confronted with ‘statistically significant evidence’, a natural reaction for a positivist is to rethink the prevailing theory and construct new theories that explain the stylized empirical facts. This reaction has given particular impetus to the development of behavioral finance or New Finance that seeks to explain deviations from market efficiency in terms of investor psychology. While strong prior beliefs still leads those with attachments to the prevailing theory to question the statistical results in favor of the new theories, claiming the results are due to ‘data-snooping’ or ‘data-mining’, others have proceeded cautiously down the new path, as evidenced in Jegadeesh and Titman (2001): “The evidence provides support for the behavioral models, but this support should be tempered with caution”.

To those not well-versed in the theories of modern Finance, discerning the distinction between technical analysis and modern Finance is something of a quandary. Technical analysis is concerned with using market-generated data to predict future price behavior. Yet, core theories of modern Finance, such as the capital asset pricing model (CAPM) and the Markowitz mean-variance optimization model, also use market generated data to form ‘optimal portfolios’. Practical implementation of, say, the Markowitz mean-variance optimization model requires the analyst to examine the time series of returns for the securities of interest together with a proxy for the risk free interest rate and the market portfolio, e.g., Eun and Resnick (1994). ‘Optimal’ portfolios are obtained by solving a quadratic optimization problem using *ex post* estimates of the means, variances and covariances of security returns. To the uninitiated, this is not substantively different than a technical analyst using the Dow theory, combined with a moving average system, to select a portfolio of speculative trading opportunities. Both approaches examine market generated data to identify equity security investment opportunities. However, the CAPM is decidedly unlike technical analysis in being derived from a coherent theory of equilibrium pricing.

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<sup>10</sup>The empirical evidence on the profitability of selling losers and buying winners is gathered from samples using returns that are generated over shorter time horizons, say one month, producing ‘under reaction’ for periods up to one year. For returns generated over longer horizons, say a year or more, ‘over reaction’ is reported where buying losers and selling winners becomes profitable.

Though there has been various attempts to extend the core theory of modern Finance to incorporate a range of other ‘factors’, e.g., Jagannathan and Wang (2002), modern Finance has not yet proposed methods for determining which factors to include in ‘the model’ that are not immune from the criticisms of data-snooping and ad hocery. In some cases, the factors that have been selected for inclusion have corresponded to measures that are widely used in the relative value analysis commonly practiced by “Wall Street” security analysts, e.g., Fama and French (1998). However, there is still an absence of a well-developed theoretical foundation for, say, the inclusion of ‘value factors’ in asset pricing models or for the apparent success of momentum strategies. By abandoning the strong belief in efficient markets and shifting the focus onto the identification of securities that generate abnormal returns, modern Finance is operating on a different battlefield. The various anomalies that have been identified may be *ex post* fictions that cannot be used to produce *ex ante* abnormal returns.

The upshot is that the efficient markets hypothesis cannot be readily abandoned by practitioners of modern Finance. It is essential to the philosophical foundation upon which the edifice of this scientific movement is constructed. It is the ‘Keynesian convention’ that is used to deal with the uncertainty arising in equity security valuation, e.g., Poitras (2002a). By adopting this convention, modern Finance is able to avoid the logical contradiction of technical analysis: how can the market discount all relevant information and prices still follow trends? Why is the trend not considered to be part of ‘all relevant information’? Technical analysts avoid this logical contradiction by claiming specialized expertise in identifying the trends while refusing to reveal the forecasting system that is being used to identify the trend due to fear of the feedback effect. Academic researchers cannot take refuge in this approach because norms of scientific analysis require at least the appearance of verification through replication.

### *Alternative Explanations*

Technical analysis has not been without adherents in the modern Finance academic community. At least since Treynor and Ferguson (1985), it has gradually been recognized that equity prices may have stochastic properties that lead to the possibility of technical trading rule profits. More recently, Lo and Hasanhodzic (2009) provide a more-or-less favorably disposed presentation of this aspect of the vernacular Finance approach with interviews detailing the background and insights of thirteen fairly prominent technical analysts. This belated realization of the possibility that ‘there

might be something in technical analysis' is unfortunate as there were credible scientific studies available around the time the efficient market hypothesis (EMH) was being formulated indicating there may be alternative explanations with better explanatory power than the EMH. These studies are both theoretical, as with Shackle (1949–1950; 1952) on non-additive probability, and empirical, as with Cowles and Jones (1937) and the associated interpretation by Rose (1951) on the 'stickiness of prices' as arising from 'rumor in the stock market'.

Rose (1951) describes the empirical situation:

If we inspect a graph of stock prices, we will observe that they do not fluctuate entirely at random in pursuing the course of the business cycle. Rather, the prices will move apparently at random for a while, and then exhibit a sudden spurt, either up or down, for several days. These spurts are the graphic manifestations of the factor of stickiness.

This behavior is consistent with the presence of more 'sequences and reversals' than for a purely random process as empirically observed by Cowles and Jones (1937) for both individual stocks and the Cowles market index for a number of different sampling frequencies, e.g., daily, monthly. An additional empirical result is also reported: there is statistically more sequences than reversals. In an odd connection to R. Elliott and the golden ratio, this resulted in a ratio of approximately 62% reversals to sequences for the important monthly sampling frequency. Though this exact result was later revised by Cowles (1960) to correct for some deficiencies in Cowles and Jones (1937) identified by Holbrook Working, the conclusions regarding the preponderance of 'sequences and reversals' and the associated use of inertia strategies to identify profitable market timing opportunities was unchanged.

If correct, the preponderance of sequences over reversals has implications for the accuracy of an *ex ante* bifurcating process as a description of the *ex post* time path. Using the 'standstill effect' of a surprise event, Shackle (1952) is able to generate such a result theoretically where the speed of reaction to downside moves is faster than for upside moves. The time reversible stochastic processes conventionally used by modern Finance academics to formulate the EMH have difficulty producing such a result even with considerable *ad hoc* calibration. The time irreversible bifurcating process also needs to resort to *ad hoc* restrictions to achieve the result, e.g., by introducing an asymmetry into the method to reset the theoretical *ex ante* decision problem following the occurrence of a bifurcation. Given the other similarities between time irreversible bifurcating processes and the general theoretical features of Shackle's framework, it appears that

such properties of stochastic price behavior are more readily described by non-additive probability notions.

The implications of using time reversible stochastic processes extend beyond theoretical considerations to include empirical testing. A number of different statistical tests can be used for determining if the randomness requirements of the EMH are satisfied. Time reversible processes permit the testing of periodicity properties. As a consequence, testing for unit roots and serial correlation are common in statistical studies of the EMH. After appropriate adjustment, e.g., converting price changes to returns, tests determine whether some simple transformation of price changes is serially uncorrelated. What has emerged from these tests is a profound concern with the higher moments of the *ex post* distribution — skewness and kurtosis. Various statistical techniques, ranging from EGARCH to Markov switching models, have been assembled to capture the unpleasant distributional properties that have been consistently and repeatedly observed in financial market data. Similar to Cowles and Jones (1937) and Rose (1951), empirical tests employing time irreversible processes explore the relationship between changes in the non-linear mean value process and the presence of sequences and reversals in the *ex post* data.

### *R.N. Elliott and Mystical Finance*

Mystical Finance encompasses technical theories that lie outside the boundaries of traditional technical analysis and New Finance. Relevant theories that lie outside these very wide boundaries all have a mystical character, as evidenced in the most important component of modern Mystical Finance: the Elliott wave theory. Christopher Kurz, the 16th century astrologer from Nuremberg that advised the Tuchers about future prices on the Antwerp bill market, is arguably a fitting candidate to be the father of Mystical Finance. Another, much earlier candidate, could be Thales, the Greek philosopher. Aristotle in *The Politics* reports that somehow (!) Thales was able to predict a bumper crop for olives in his locale and was able to take leases on all available olive presses at low prices well before the crop materialized, e.g., Poitras (2009a). When the bumper crop materialized, Thales was able to make a fortune, subleasing the presses at high prices. Whatever the origins, the essence of these theories is aptly described by the title of the last book by R.N. Elliott (1871–1948): *Nature's Law—The Secret of the Universe* (1946; Prechter 1994).

The line between traditional technical analysis and Mystical Finance is blurry. For example, basic elements of the Elliott wave theory are derived



from the Dow theory which is a central concept in traditional technical analysis. Triangles, wedges and rectangles, price formations that play a key role in the Elliott wave theory, have corresponding notions in the Dow theory and other forms of traditional technical analysis, e.g., Frost and Prechter (1990, p. 165). Where mysticism appears is in the next step: connecting the method of analysis with a divine reality, God, Absolute of Nature or some other such universal construct. “Elliott discovered that the ever-changing path of prices reveals a structural design which in turn reflects a basic harmony found in nature. From this discovery, he developed a rational system of market analysis” (Frost and Prechter 1990, p. 17). Where Elliott was concerned with the universal element of the cyclic movements in the US stock market, Kurz connected price movements in the Antwerp bill market with the astrological movements of heavenly bodies.

Instead of the mysticism of astrology, Elliott substitutes ‘Nature’s Law’ which is based on the Fibonacci sequence (Elliott 1946, p. 229):

All human activities have three distinctive features — pattern, time and ratio — all of which observe the Fibonacci Summation Series. Once the waves can be interpreted, the knowledge may be applied to any movement, as the same rules apply to the price of stock, bonds, grains, cotton, coffee and all other activities previously mentioned.

For Elliott the Fibonacci sequence is: 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, etc. “The sum of any two adjoining numbers equals the next higher number. For example  $3 + 5 = 8$ . The waves of every movement coincide with these numbers”. From this observation, Elliott is able to construct some predictions about the behavior of stock market prices or, more precisely, stock market indexes. Elliott did not give much concern to the stock market until quite late in life. His main academic contribution prior to this time was *Tea Room and Cafeteria Management* (Elliott 1926).

It was Rhea (1932), *The Dow Theory*, that sparked Elliott’s initial interest in predicting the market. As such, Elliott can be considered an offshoot of the Dow theorists. In contrast to Hamilton, Rhea advocated using the Dow theory to predict secondary as well as primary trends in the equity market. Prechter (1994, p. 50) observes that Elliott’s:

essential path of inquiry, i.e., looking for patterns in aggregate stock price movement, was undoubtedly directed initially by exposure to tenets of the Dow Theory. However, Elliott’s ultimate discovery was all his own, as over a period of several years he painstakingly uncovered the Wave Principle of market behavior by studying empirical evidence.

The impact of Rhea and the additional input of Elliott is apparent in the following table which depicts a complete stock market cycle conforming to the Elliott wave theory (Frost and Prechter 1990, p. 21):

Subdivisions of Cycle degree	Bear market	Bull market	Complete cycle
Cycle	1	1	2
Primary waves	3	5	8
Intermediate waves	13	21	34
Minor waves	55	89	144

One full stock market price cycle is composed of one bear and one bull cycle. The bear cycle is composed of three primary waves followed by the bull cycle that has five primary waves. And so it goes, conforming to the dictates of the Fibonacci sequence.

One of the strong predictions of the Elliott wave theory deals with the ratio of terms in the Fibonacci series. In particular, if the series takes the form

$$1, 1, 2, 3, 5, 8, 13, 21, \dots, u_n, u_{n+1}, \dots$$

where

$$u_n = u_{n-1} + u_{n-2}$$

then:

$$\lim_{n \rightarrow \infty} \frac{u_{n-1}}{u_n} = \frac{\sqrt{5} - 1}{2}.$$

Elliott gave some attention to recognizing that this limit is the ‘golden ratio’. Elliott traced the historical origins of the golden ratio back to the Egyptians and the dimensions of the Great Pyramid of Gizeh. Elliott claims both Pythagoras and Fibonacci learned of the golden ratio on visits to Egypt. Whether this particular historical interpretation is correct does not change the result that knowledge of the ratio first appeared in antiquity. Using the basic geometry of a line segment the result is easy enough. Divide a fixed line segment in two. The golden ratio appears when the ratio of the smaller segment to the larger segment equals the ratio of the larger segment to the whole line. Recognizing that the golden ratio is an irrational number approximately equal to 0.618, it follows that in the Elliott wave theory the length of time that the three primary waves of the bear market correction will last is about 61.8% of the time involved in the five primary waves of the subsequent bull market.

## 6.2 Traditional Technical Analysis

### 6.2.1 The Dow Theory

The Dow theory has a long pedigree stretching back to Charles Dow and the creation of the Dow-Jones rail and industrial averages circa 1897.<sup>11</sup> Edwards and Magee (1992, p. 13) make the claim: “The Dow Theory is the granddaddy of all technical market studies”. The first key historical figure in the development of the theory is Charles Dow, founding editor of the *Wall Street Journal*. Dow originated the basic approach of using stock market averages to predict future movements in the market. The main source of information about Dow’s views is fifteen *Journal* editorials written between 1899 and 1902. (Dow did not publish any books on the subject or make reference to the ‘Dow’s theory’.) Reference to ‘Dow’s theory’ can be traced to a collection of these editorials that was published by Samuel Nelson Armstrong, an author of practical books on finance and a personal friend of Dow, under the title *The ABC of Stock Speculation*. Despite having started the ball rolling, Dow did not contribute much detail to the theory that has come to bear his name. Shortly after Dow’s death in 1902, William P. Hamilton assumed the editorship of the *Journal* and developed the bulk of the theoretical structure for the Dow theory, mostly contained in *Journal* editorials published between 1908 and 1929.<sup>12</sup> Though Hamilton did write a book outlining the theory (Hamilton 1922), the essential primary source of his views on the theory are these editorials that discussed and forecasted major trends in U.S. stock markets using the rudiments of the Dow theory. Brown *et al.* (1998) put the number of these editorials at 255.

One of the oddities of the Dow theory is the untimely deaths of the major historical figures responsible for developing the theory. Just as Dow

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<sup>11</sup>A useful source on the history of the Dow theory is an article by Richard Russell that can be found on the website [www.dowtheoryletters.com](http://www.dowtheoryletters.com). The following discussion of Schaefer’s approach to the Dow theory is based on Russell’s discussion of Schaefer’s advisory newsletters that is contained in that article. Edwards and Magee (1966, Chaps. 3–5) has a useful overview of the main elements of the theory. This reference is to the fifth edition. There was not much change between this and the final seventh edition (1997) of this classic text.

<sup>12</sup>There is some debate over the precise starting date for Hamilton’s contribution of the Dow theory. Brown *et al.* (1998) date the beginning in 1902, the year of Dow’s death. However, Clement (1997) observes that, while joining the newspaper in 1899, Hamilton did not have the job of editing the editorial page of the *Journal* — the source of early Dow theory prognostication — until 1908. Due to the presence of two brief tenures by others as *Wall Street Journal* editors following the death of Charles Dow, Hamilton was the fourth editor of the *Journal*. Hamilton held this position until his death in 1929.

died shortly after bringing the theory on line, Hamilton died in December 1929 shortly after writing his last editorial on 25 October 1929 titled: 'The Turn of the Tide'. The demise of Hamilton marks a turning point in the evolution of the Dow theory from the preserve of *Journal* editors into the domain of the investment advisory industry. This stage begins with Robert Rhea, a key figure in detailing, refining and popularizing the theory as it had been developed by Hamilton, e.g., Rhea (1932). Though Rhea closely followed Hamilton in his explanations of the theory, Rhea had the instinct to develop the '*art*' of the Dow theory. This instinct permitted Rhea to call the bottom of the bear market almost exactly on 8 July 1932. Rhea developed techniques for using the averages for trading secondary, as well as primary, market trends. In November 1932, Rhea launched 'Dow Theory Comment', an investment advisory service that attracted considerable notoriety for being correctly bullish when the bears dominated market opinion. Rhea is also credited with correctly calling the bear market of 1937, a prognostication that added considerably to Rhea's already significant standing on Wall Street.

Throughout the 1930s, Rhea had been afflicted by tuberculosis, a disease that took his life in 1939. With the absence of its leading proponent in the investment advisory industry and without promotions on the editorial page of the *Journal*, it was not until after WWII that the Dow theory was rejuvenated by George Schaefer. This revival can be dated from 1948 when Schaefer started an investment advisory service, 'Schaefer's Dow Theory Trader'. Like Rhea, Schaefer had a keen instinct for the 'art' of using the Dow theory to predict stock market trends. In June 1949, shortly after starting the advisory service, Schaefer correctly called, almost to the day, the beginning of the major bull market that was to continue until 1966. In his advisory service newsletter, Schaefer used a 'new version' of the Dow theory to detail reasons for the start of a major bull market. Schaefer continued to be bullish throughout the seventeen year bull market, advising client's to accumulate stocks on the numerous dips and drawbacks associated with the secondary movements of the market. In a remarkable prognostication, Schaefer turned bearish in early 1966 and held that position until his death, by suicide, in 1974. In another quirk in the murky history of the Dow theory, the year of Schaefer's death marks the beginning of another primary bull market movement.<sup>13</sup>

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<sup>13</sup>Russell traces the bull market trend that ended in 1999 to a beginning in 1982 (Du Bois 2001). Much like Schaefer, the primary source of Russell's views on the Dow theory are an

As evidenced by continuing references to the Dow theory in the popular financial media, the theory continues to have a strong following of adherents in present day Wall Street, e.g., Du Bois (2000, 2001). The essence of the Dow theory is reflected in the words of Richard Russell, the modern version of the Dow theory investment advisor (see [www.dowtheoryletters.com](http://www.dowtheoryletters.com)): “[The] Dow theory can’t be summed up in one or two sentences. It’s more of an art form than anything specific. It requires a lot of interpretation” (Du Bois 2001). This is consistent with the Graham and Dodd view that ‘intelligent technical analysts’ adopt the view that the forecasting methodology employed has to be viewed as an art form and not a science. Given that an art form cannot be precisely defined, it is still possible to sketch the basic conceptual elements. The first element in the Dow theory is that there are ‘*three simultaneous movements in the market*’ (Russell 1960, p. 4–5):

The first [is] the great primary trend or tide. In a bull market, for example, this is a broad upward movement, interrupted by frequent reactions. The primary trend may last from one year to a great many years. The next movements are the so-called secondary reactions, which reverse and correct the tidal moves. They usually last from three weeks to three months, and then retrace one-third to two-thirds of the previous uncorrected primary moves. The final movements are the daily moves. These minor fluctuations admittedly can be manipulated by the news of the day. Although the least important, they are the ones to which the public pays the most attention. The single movement which every investor must be aware of at all times is the primary trend. Investors should always invest with this primary tide.

The Dow theory is a body of techniques that have been developed — partly based on empirical observation, partly based on intuition — to identify the primary trend in the stock market. As such, the Dow theory is concerned with timing the overall market and using the predictions to guide portfolio composition.

Since the inception, Dow theorists have made an analogy between the three movements in the market and movement of the ocean. The primary trend is like the tide while the secondary reactions resemble the waves with the daily movements being ripples. As Russell observes (Du Bois 2001):

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investment advisory newsletter — ‘Dow Theory Letters’ — that Russell has produced continuously since 1958. Russell (1960) contains a collection of early newsletters. In addition to these sources, there a number of interviews and columns that have appeared in *Barron’s*.

“It isn’t the waves that make or break you in this business, it’s the great ocean tide of the market”. Sail with the tide, not against it. While the analogy to movements of the tide is helpful, the analogy is also somewhat misleading. Unlike the gravitational pull of the moon that determines the tides and allows for accurate prediction, the primary trend in the stock market is considerably more difficult to determine. Dow theorists approach this problem by dividing the primary trend into phases. In the case of a primary bull market trend (Russell 1960, p. 5):

Phase one is the rebound from the depressed conditions of the previous bear market. Here stocks return to known values. In the second and longest phase, shares advance in recognition of improving business and a rising economy. During the third phase they spurt skyward on the hopes and expectations of a continuing rosy future. This is the traditional period of great prosperity and unbounded optimism. It is here that the public enters the market wholeheartedly for the first time. The low-priced “cats-and-dogs” historically make great moves in this third phase, and market volume becomes excessive.

This distinction between the *three types of market movement* — *primary trend, secondary reaction and daily fluctuation* — and *three phases of a primary trend* — *recovery, recognition and exuberance* — can be a source of confusion.

Another potential source of confusion about the Dow theory arises with the method used for determining whether and when the primary trend indicates a bull market or a bear market. The basic notion, derived from Hamilton and Rhea, is the concept of *confirmation*. Russell (1960, p. 5–6) describes the concept:

Under the Dow theory, it is a bullish sign when successive rallies penetrate previous high points, and ensuing declines terminate above preceding lows. It is a bearish indication when rallies fail to penetrate earlier highs, and ensuing declines carry below their former lows. It is crucial to remember that the movements of both Rail and Industrial Averages always must be considered together. The action of one Average must be confirmed by the other before reliable inferences can be considered. A penetration of one Average unconfirmed by the other is meaningless for prediction purposes and frequently can be deceptive.

The concept of confirmation relates to predictions of future market movements based on analysis of changes in the Dow–Jones Industrial Average (DJIA) (see Table 2.1) having to be considered in conjunction with an analysis of changes in the Dow–Jones Transportation Average (DJTA) (see Table 6.1). The confirmation of these two signals is usually expected to be

Table 6.1 Dow Jones Transportation Averages, 25 April 2003.

Company	Exchange	Ticker Sym.	Style	Primary Group	Mkt. Cap.	Wghtg.	US\$ Close
Airborne Inc.	New York SE	ABF	VAL	Air Freight	Sml. Cap.	3.6311	19.89
Alexander & Baldwin Inc.	NASDAQ NMS	ALEX	VAL	Marine Transport	Sml. Cap.	4.794	26.26
AMR Corp.	New York SE	AMR	VAL	Airlines	Sml. Cap.	0.8033	4.4
Burlington Northern Santa Fe Corp.	New York SE	BNI	VAL	Railroads	Lrg. Cap.	5.0916	27.89
CNF Inc.	New York SE	CNF	VAL	Trucking	Mid. Cap.	5.3983	29.57
Continental Airlines Inc. CI B	New York SE	CAL	GRO	Airlines	Sml. Cap.	1.5335	8.4
CSX Corp.	New York SE	CSX	VAL	Railroads	Mid. Cap.	5.6703	31.06
Delta Air Lines Inc.	New York SE	DAL	N/A	Airlines	Mid. Cap.	2.1852	11.97
FedEx Corp.	New York SE	FDX	GRO	Air Freight	Lrg. Cap.	10.7326	58.79
GATX Corp.	New York SE	GMT	VAL	Industrial Services	Sml. Cap.	3.224	17.66
J.B. Hunt Transport Services Inc.	NASDAQ NMS	JBHT	N/A	Trucking	Sml. Cap.	6.2599	34.29
Norfolk Southern Corp.	New York SE	NSC	VAL	Railroads	Mid. Cap.	3.7607	20.6
Northwest Airlines Corp.	NASDAQ NMS	NWAC	GRO	Airlines	Sml. Cap.	1.3071	7.16
Roadway Corp.	NASDAQ NMS	ROAD	N/A	Trucking	Sml. Cap.	6.6561	36.46
Ryder System Inc.	New York SE	R	VAL	Transportation Services	Sml. Cap.	4.3412	23.78
Southwest Airlines Co.	New York SE	LUV	GRO	Airlines	Lrg. Cap.	2.7585	15.11
Union Pacific Corp.	New York SE	UNP	VAL	Railroads	Lrg. Cap.	10.8367	59.36
United Parcel Service Inc. CI B	New York SE	UPS	GRO	Air Freight	Lrg. Cap.	11.0484	60.52
USFreightways Corp.	NASDAQ NMS	USFC	VAL	Trucking	Sml. Cap.	5.1226	28.06
Yellow Corp.	NASDAQ NMS	YELL	VAL	Trucking	Sml. Cap.	4.8451	26.54

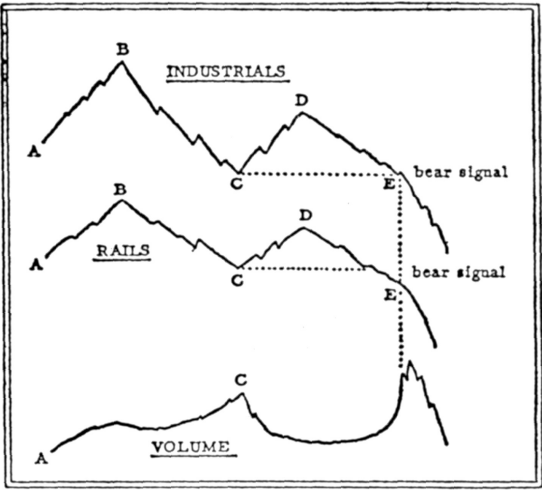


Fig. 6.1 Example of a Dow Theory Confirmation Signal.  
Source: Russell (1960).

accompanied by a high level of trading volume on the confirmation date (see Fig. 6.1 for an illustration). When asked to describe the Dow theory, it is this ‘confirmation of the industrial and transportation averages’ statement of the theory that will typically be identified. Supplementary interpretation concepts such as penetration, reversal, break-out and so on follow appropriately.

As is evident from an inspection of the five year chart for the DJTA and DJIA index levels (Figs. 6.2 and 6.3) and 10-year chart for percentage changes in both index level series (Fig. 6.4), *identification of confirming signals* in the secondary movements in the DJIA and DJTA is often not an obvious exercise. For example, was a confirmation signal achieved on 11 March 2003 in Fig. 6.4. Though it came close, the low in the DJTA index level that occurred in March 2003 was not quite confirmed as the DJIA did not quite reach a new low on that date. The volume on that date was also not consistent with the ‘climax of volume’ signal for a change in primary movement. The picture is clearer on the primary trend. Comparing Figs. 6.2–6.4 with the stylized example in Fig. 6.1, it appears that the Dow theory has produced a strong signal for the end of the primary bear market trend that began in May 1999 and included the 2003 secondary bear market trend low.





Fig. 6.2 Dow Jones transportation index, 2004–2009 with 100 and 200 day MA.



Fig. 6.3 Dow Jones industrial index, 2004–2009 with 100 and 200 day MA.

The stock market trading environment has changed significantly since Dow, Hamilton and Rhea developed the corpus of the theory.<sup>14</sup> For instance,

<sup>14</sup>The possibility of a substantive change in the Dow theory was recognized by Richard Russell in a interview published in *Barron's* on 12 June 2000 (Du Bois 2000). Speaking of the first phase of the bear market that followed the change in primary market movement in May 1999, Russell observes: “In some ways, the current first phase is different from any other I’ve ever seen . . . Because it has lasted longer, because many more individuals and institutions are involved . . . and because a new phenomenon, the Internet, has emerged and is obviously changing the world. Then there’s volatility. I’ve never seen anything



Fig. 6.4 Dow Jones industrial and transportation indexes, 1999–2009.

as illustrated in Table 6.1, the DJTA is no longer an index composed entirely of railway companies. This change has been effective since 1970. The implications of the significant change in the composition of the DJTA, when compared to the all-railway Dow (Railway) Transport index of Dow, Hamilton and Rhea, is difficult to formalize. The ability of leading Dow theorists to predict major primary market changes in 1929, 1932, 1974, 1982 and 1999 is strong evidence that the change in the DJTA did not substantively impact the predictive ability of the Dow theory. However, it is possible that the connection between the DJTA and DJIA may have been changed significantly by the impact of the 9/11 shock on the airline industry — if only because the impact on airline valuations reduced the share of this component in the DJTA. Perhaps this created an instance in 2003 where the theory failed to give an unambiguously clear signal. All indications are that the structural changes in the securities markets and the economy from 2003–2009 have given the Dow theory new life in the form of a primary bear market low in March 2009.

like what we have now. Among the reasons for it are day-traders moving in and out of stocks”. Structural changes such as the trading ‘circuit breakers’ introduced following the market collapse of October 1986 may have altered the underlying dynamics sufficiently to prevent a strong signal for the end of a bear market to emerge.

Fortunately, there are other elements of the Dow theory that can be used to provide guidance about whether the traditional confirmatory signal has been altered by structural changes. Those with only a casual exposure to the Dow theory are usually surprised to discover that there is considerable divergence among Dow theorists about the central role of the confirmation feature of the theory. *Old-style Dow theorists*, followers of Hamilton and Rhea, base the art of interpreting the averages primarily on further properties of the charts. As Rhea observes (Russell 1960, p. 7): “Beginners frequently make the mistake of basing conclusions wholly on the matter of penetration. Familiarity with the co-related factors of duration, extent, activity, divergence, and secondary implications of primary bull markets is needed to make the correct diagnosis”. Yet, even old-style Dow theorists do not focus exclusively on the behavior of the averages, seeking also to identify elements that are expected to be present when there is a change in the primary movement. If these elements are not present, then confirmation of the averages alone is not sufficient.

For old-style Dow theorists a change in primary movement of the market from bull to bear can only occur during the third phase of the bull market. Rhea describes the characteristics of the third phase of a bull market:

This is the time when brokers and soothsayers prosper, and when an excited public, lured by the bait of advancing prices, buys stocks without regard to values, basing their action on nothing more than hopes and expectations . . . this is the phase where worthless stocks are bought for no other reason than because they look cheap, and because gamblers hope they will double in price. This condition has always prevailed in the third phase of bull markets.

If these types of activities are not witnessed in the marketplace, then confirmation signals are likely to be false, second phase indications of a change in the primary market movement. Unfortunately, the three phases are not symmetric across bull and bear markets. While the characteristics of the three phases of a bull market are readily specified, guidance from the Dow theory about the three phases of a bear market is less precise. It is recognized that the extent and duration of a primary bear market will be shorter than for a primary bull market, with the drop in the averages being much more rapid in a bear market than the rise in the averages during a bull market.

*Modern Dow theorists*, such as Schaefer and Russell, put considerably less weight on the averages in determining the primary market movement. For example, Schaefer states: “A study of the Averages themselves

can be highly rewarding. But in my opinion, a forecast based on past movements of the Averages cannot be conclusive. Predictions of events to come are more reliable if they can be reinforced by analysis of other technical and more conclusive factors". These other factors include: the 200 day moving average of the Dow (see Fig. 6.3); the short interest ratio; the advance-decline line; market sentiment; market phases; and the bond yield cycle. Russell takes this approach even further (Du Bois 2001): "[confirmation of the averages helps] to identify the primary trend. However, value, dividend yield and other factors also play an important role. Without understanding all of them you're lost". Unlike Hamilton and Rhea who promoted active trading on secondary phase reactions in bull and bear markets, Schaefer advised: "Once stocks are purchased, both the minor and secondary movements in the market should be completely disregarded". Second phase pull-backs in a bull market are buying (not rebalancing) opportunities, while second phase run-ups in bear markets are selling opportunities.

Starting from the contributions of Schaefer, the modern form of the Dow theory makes 'value' the operative word. As Russell observes: "All other Dow theory considerations are secondary to the value thesis. Therefore, price action, support lines, resistance, confirmations, divergence — all are of much less importance than value considerations, although critics of the theory seem totally unaware of that fact". The transformation of the old-style Dow theorist to the modern Dow theorist can be gleaned from statements made by Russell in April 2001 about the previous bull market and the state of the on-going bear market. The likelihood of non-confirmation at market peaks is explicitly acknowledged (Du Bois 2001):

the long bull market that began in 1982 ended on May 12, 1999 when the DJIA and the Transports both hit peaks. The Industrials eventually topped out at 11,722.98 in January 2000, but the Transports failed by a wide margin to confirm that record high. This bear market probably won't end until there's a final non-confirmation on the downside.

This statement suggests the possibility that the global low point for the DJIA in a primary bear market trend may not be confirmed by the DJTA. Rather the bottom could come when the DJTA hits a global low and the DJIA hits only a local low that is followed by an, unconfirmed, global low. This is something of a disconnect from the old-style Dow theory that, implicitly, assumes the DJTA and DJIA confirmation would be associated with global values, as subsequently happened with the global low in March 2009.

Another element distinguishing old-style and modern Dow theorists is the emphasis on using measures of value to supplement conventional analysis of the averages. This emphasis on value measures is evident in Russell's April 2001 analysis of the S&P 500 (Du Bois 2001):

At its recent 1166, the S&P yielded about 1.2%. Were the yield to quadruple to 4.8% — and its been higher than that in the past — the S&P would drop to about 300. Interestingly, the S&P now trades at over three times revenues, six times book value and 75 times dividends. These figures are well above peaks seen at previous bear-market tops, and illustrate just how overvalued the S&P 500 is.

However, there are still key elements of the old-style Dow theory left in the analysis:

Bear markets usually last about 25%–33% as long as the preceding bull market. Assuming the recent bull market ran from a low in 1982 to a peak in 1999, we're talking 17–18 years. By this measure, I expect the decline to last four or five years, until 2005 or 2006. One possible difference this time is the speed at which the Nasdaq has plunged. If the Dow picks up momentum on the downside, the bottom could arrive sooner than 2003.

In considering the potential length of the current bear market, Russell still depends on the old-style notions of extent and duration.

And what advice was Russell dispensing in April 2001? After acknowledging that he had already shifted his personal portfolio into U.S. Treasury bills, Russell observes:

Take this bear market seriously. It's never too late to do the right thing. In a primary bear market, the right thing is to play it safe. That means getting out of almost all common stocks and into US government paper. With cash in hand, you boost your buying power at the eventual bottom.

In retrospect, this advice was able to avoid the large drop in stock values but did not take advantage of the increase in bond prices associated with the downward shift in the Treasury yield curve that took place over the 2001–2002 period. This said, the quality of the market prediction is solid. To provide context to the predictions that Russell was making consider the following:

resistance to believing we're in a bear market is mind-boggling. People still seem to be hanging on for the "long haul". This really is a tragedy. The losses in the average portfolio must be horrific. Foolish optimism and the speed of the Nasdaq decline literally have "locked in" millions of investors, the people who buy individual stocks and mutual

funds... Way back at the turn of the 20th century, Charles Dow wrote that the most difficult concept to teach people is the inevitability of change. Sometimes the simplest ideas are the hardest to get across.

It is difficult to examine these notions and not be puzzled as to why so little attention has been given to the Dow theory in academic Finance.

This is not to say that the Dow theory has been completely ignored in modern Finance.<sup>15</sup> As Brown *et al.* (1998, p. 1311) recognize, empirical testing of the Dow theory was the impetus for Cowles (1934) “a landmark in the development of empirical evidence about the informational efficiency of the [stock] market”. However, unlike Cowles where it is found that “market timing based on the Dow theory results in returns that lag the market”, Brown *et al.* arrive at the opposite conclusion:

we review Cowles evidence and find that it supports the contrary conclusion — the Dow theory, as applied by Hamilton over the period 1902 to 1929, yields positive risk-adjusted returns. The difference in the results is apparently due to the lack of adjustment for risk. Cowles compares the returns obtained from Hamilton’s market timing strategy to a benchmark of fully invested stock portfolio. In fact, the Hamilton portfolio, as Cowles interprets it, is frequently out of the market. Adjustment for systematic risk appears to vindicate Hamilton as a market timer.

Yet, all this speaks to old questions surrounding the Dow theory and has only indirect implications about the prospects of using the Dow theory in contemporary securities markets.

Brown *et al.* begs a number of questions about whether the Dow theory is a viable method of market timing and about the feasibility of testing the Dow theory over a given sample. For example, there is the general question about whether it is possible to construct acceptable empirical tests of the Dow theory. Both Cowles and Brown *et al.* approach this problem by examining the prognostications of a specific, albeit important, early proponent of the Dow theory, W.P. Hamilton. However, at least since Stansbury (1960) and Bishop (1961) it has been recognized that the Dow theory has had to evolve through time, as market conditions and institutions change. As such, there is no ‘functional form’ that is applicable to the Dow theory and can

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<sup>15</sup>The Dow theory of technical analysis is not related to the ‘Dogs of the Dow’ theory that has been explored in some academic studies, e.g., Hirschey (2000), McQueen *et al.* (1997), and Visscher and Fillbeck (2003). Poitras (2005, pp. 561–564) provides more discussion of this stock selection strategy that recommends a portfolio composed of the 10 highest dividend yielding stocks in the Dow Jones Industrial Average.

be estimated using, say, regression analysis. Rather, there are many Dow theorists, each with a distinct interpretation of what the theory says. While it is possible to estimate whether a basic feature of the Dow theory, such as the DJTA/DJIA confirmation signal, is capable of generating trading profits from market timing, the theory is more appropriately seen as a general qualitative guide to investment strategy as opposed to being a source of hard-and-fast trading signals.

### 6.2.2 *Charting and Moving Average Systems*

#### *Types of Charts*

The modern Dow theory is something of an oddity in the realm of technical analysis. While it is predicated on the basic notion of all technical analysis that prices move in trends, the objective is to predict long-term movements in stock market averages. In contrast, most technical analysis is concerned with shorter trading horizons, usually focusing on the performance of individual stocks or commodities. As such, the primary objective for much of this type of technical analysis is speculation whereas the Dow theory is more relevant as a supplement to equity security investment strategy. Despite the rather chauvinistic attitude of fundamental purists and modern Finance believers, it is difficult to deny that some aspect of ‘charting’ does not enter into every practical equity security valuation or investment selection decision. Inspection of a three month, one year or three year price history is a typical first step in determining the value of a common stock. Technical analysis attempts to bring more structure to this process. In the absence of a unified theoretical foundation, the resulting vernacular procedures are derived inductively. By construction, technical analysis will be subject to the problems of using *ex post* analysis for making *ex ante* decisions.

Even if an analyst has little belief in the efficacy of the various procedures used in technical analysis, it is difficult to deny that there are large numbers of traders that employ such techniques. At least in the short-run, the activity of these traders can impact the price of specific securities.<sup>16</sup>

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<sup>16</sup>The statement cannot be taken too literally. In general, it is not clear that technical analysts will move prices since technicians are not a homogeneous group. There are many different types of technical analysis and even analysts using the same approach may come up with conflicting buy and sell signals.

As a consequence, even rigid nonbelievers in technical analysis can benefit from basic knowledge about certain elements of the approach. The starting point and, in many cases, the ending point for technical analysis is charts. As Edwards and Magee (1966, p. 7) observe:

Charts are the working tools of the technical analyst. They have been developed in a multitude of forms and styles, to represent graphically almost anything and everything that takes place in the market or to plot an “index” derived therefrom. They may be monthly charts on which an entire month’s trading record is condensed into a single entry, or weekly, daily, hourly, transaction, “point-and-figure”, etc. They may be constructed on arithmetic, logarithmic or square-root scale, or projected as “oscillators”. They may delineate moving averages, proportion of trading volume to price movement, average price of “most active” issues, odd-lot transactions, the short interest, and an infinitude of other relations, ratios and indexes — all technical in the sense that they are derived, directly or indirectly, from what has actually been transacted on the exchange.

Though it is possible to use other ‘working tools’ than charts to accomplish the same result, e.g., Lo *et al.* (2000), the bulk of technical analysis is presented in terms of chart interpretations. As a consequence, in order to explain and assess technical analysis it is necessary to examine charting techniques.

Outside the realm of technical analysis, the most commonly observed chart for common stocks is the ‘*close-only*’ chart. This type of chart is simply a time series of closing prices plotted using an arithmetic scale. The frequency of observation is typically daily, weekly or monthly depending on the length selected for the time period of interest. Observations for longer intervals, such as weekly or monthly, are usually for specific days, e.g., every Friday for weekly, though averages can also be used. Sometimes close-only charts are used because intra-day data is not available. In other cases, the close-only chart is selected because the technical analyst believes that the inclusion of high-low, open and other information on the chart tends to cloud the picture, i.e., the closing price is the appropriate summary of the key information. However, Schwager (1996, p. 21) reflects the typical view: “many important chart patterns depend on the availability of high/low data and one should think twice before ignoring this information”.

While close-only charts can be used for various purposes, there are three other basic chart types that are more commonly used for doing basic technical analysis: bar charts (see Fig. 6.5); point-and-figure charts; and Japanese candlestick charts (see Fig. 6.6). *Point-and-figure charts* (not discussed



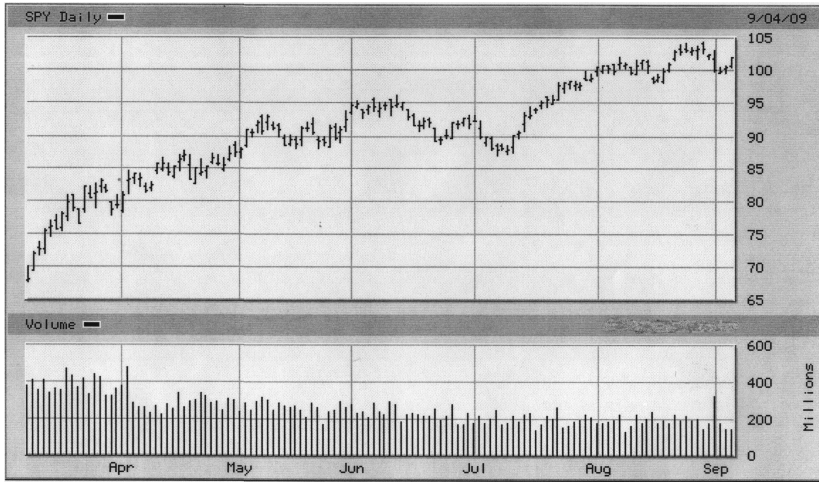


Fig. 6.5 S&P 500 (SPY) daily OHLC bar chart, 3/4/09 – 9/4/09.

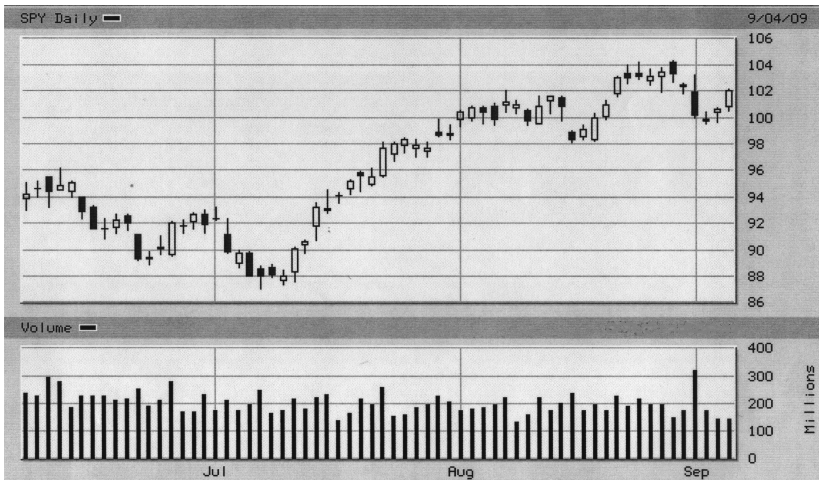


Fig. 6.6 S&P 500 (SPY) 3-month daily candlestick chart, 6/4/09 – 9/4/09.

here) are specialized charts more commonly used in futures markets, particularly by floor traders and day traders, than in stock markets.<sup>17</sup> These

<sup>17</sup>One service that does make extensive use of point and figure charts for stock analysis is Investor's Intelligence. Examples of point and figure charting for stocks can be viewed at the service website: [www.investorsintelligence.com](http://www.investorsintelligence.com). Standard drawing of trend lines applies to point and figure charts in the same fashion as bar charts and candlestick

charts do not take account of time but, rather, view trading as a continuous process. For technical analysis of security prices, *the bar chart* comes in two formats with the *high-low-close (HLC) chart* being the most common type. For a daily HLC bar chart each day is represented by a vertical line connecting the high and low prices for the day with a small horizontal line indicating the close. As indicated in Fig. 6.5, the traditional bar chart can be augmented to an *open-high-low-close (OHLC) bar chart* that indicates the open with small horizontal lines on the right (left) side of the bar for the close (open). Bar charts for longer intervals, such as a weekly or monthly bar chart, are analogous. For, say, a weekly bar chart the vertical line represents the high and low for the week with the small horizontal line representing the final closing price for the week. Because of the different appearance of charts for different sampling intervals, it is common for daily, weekly and monthly bar charts to be examined when doing a technical analysis for a given security.

Though the history of candlestick charts in Japan predates bar charts and point-and-figure charts, this method of charting was virtually unknown outside of East Asia prior to Nison (1991). Compared to bar charts, *candlestick charts* are more versatile and have more rules to generate signals than HLC bar charts. In effect, a candlestick chart contains all the information available in a close-only or HLC bar chart and more (see Fig. 6.6). Because a candlestick chart has more information it is also somewhat more complicated and requires more preparation effort. Such chart formats are available at publicly accessible internet futures charting services such as [www.futuresource.com](http://www.futuresource.com), and are increasing available at no-pay-for-use common stock charting services, e.g., [www.bigcharts.com](http://www.bigcharts.com). The traditional HLC bar chart is still the standard format for stock charts. Casual inspection of a traditional bar chart reveals that while the high, low and close are indicated, there is no information about the open. While the OHLC charts does not reveal the relationship between open and close, the candlestick format aids signal identification. The information provided in the candlestick chart is a thin line for a given day that gives the high and low while the white/green and black/red boxes — called ‘real bodies’ — reflect the open and close. A black/red (white/green) real body indicates that the open was above (below) the close. The top of the real body indicates the open (close) with the bottom indicating the close (open).

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charts. Because technical analysis is not limited to spot (cash) market trading, a number of important technical analysis sites are concerned with futures prices.

Candlestick charting has many aesthetically pleasing features. The nomenclature is one such feature. For example, the part of the thin line that lies above the real body is referred to as the ‘upper shadow’ with the part of the thin line below the real body being the ‘lower shadow’. If the open and close are equal or approximately equal then there will be no real body. This is a *doji* — literally translated as ‘indecision’. Dojis provide a signaling mechanism that is not available in bar charts. For example, the presence of a doji following a large white candle is a strong signal that a rally is stalling. Another key feature is *the hammer* which occurs where: the real body is at the upper end of the trading range (the color is not important); has a long lower shadow that is more than twice the height of the real body; and, little or no upper shadow. A hammer occurs when the market opened near the high, traded down during the day and rallied to close near the high. This is a bullish signal for near term trading. Of the three distinct hammers in Fig. 6.6 two were followed by a strong up move the next trading session with one followed by a down session. There are numerous other features of candlestick charts, e.g., dark cloud cover, hanging man, morning star. However, discussion of these aspects would require more attention than is warranted here.<sup>18</sup> More detail on these issues can be found in Nison (1991, 1996) and at websites dedicated to technical analysis such as [www.marketsource.com](http://www.marketsource.com).

### 6.2.3 Chart Patterns

A key notion of technical analysis is that prices follow trends. Charts are used for identification of trends. As it turns out, trend identification is considerably more complicated than drawing a line on a chart. The process becomes subjective almost immediately. Consider the definition of a trend. Edwards and Magee (1966, p. 47) observe:

Stock prices move in trends. Some of these trends are straight, some are curved; some are brief and some are long-continued; some are irregular and poorly defined and others are amazingly regular or “normal”, produced in a series of action and reaction waves of great uniformity. Sooner

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<sup>18</sup>In addition to requiring considerable space for developing the requisite notions, there is also relatively little information available on the profitability of the various candlestick chart patterns. One study reported by Schwager (1996, pp. 296–305) provides results that “were not encouraging . . . The test . . . does not prove that candlestick charts have no value, but rather that a simplistic interpretation of candlestick patterns is not profitable”. It seems that, like other forms of technical analysis, candlestick charts are sensitive to whether there is a trend or a trading range in the underlying price series.

or later these trends change direction; they may reverse (as from up to down) or they may be interrupted by some sort of sidewise movement and then after a time proceed in their former direction.

Recognizing that there are numerous possible approaches to specifying trends, consider the commonly used definition: an uptrend is defined by a sequence where each ‘high’ is followed by a ‘high’ that is higher and each ‘low’ is followed by a ‘low’ that is higher. Similarly, a downtrend is defined by a sequence where each ‘high’ is followed by a ‘high’ that is lower and each ‘low’ is followed by a ‘low’ that is lower. The ‘highs’ and ‘lows’ — often referred to as ‘relative highs’ and ‘relative lows’ — occur because price charts appear as jagged lines.

In drawing a trend line for a downtrend it is conventional to connect the sequence of lower relative highs. For an uptrend, the trend line will conventionally connect the sequence of relative lows. Where a trend line is drawn for both the relative lows and relative highs the resulting (hopefully) parallel lines form a **trend channel**. For a trend channel, the upper line is referred to as the ‘resistance line’ and the lower line as the ‘support line’ (Kaufman 1978, p. 139). The breaking of a trend line by a relative high or low is an indication that the trend *may* have ended. The practical difficulty that can arise with this exercise of defining a trend line is illustrated in Fig. 6.5 that provides 6 month bar chart for the S&P 500 (SPY). The trend line for this chart indicates that there is an identifiable uptrend over the period. Similarly, there clearly is an identifiable downtrend and uptrend on the five year DJIA chart in Fig. 6.3. Despite this, Schwager (1996, p. 25) captures the conservative conclusion that needs to be drawn from the breaking of a trend line: “It should be emphasized... that the disruption of the pattern of higher highs and higher lows (or lower highs and lower lows) should be viewed as a clue, not a conclusive indicator, of a possible long-term trend reversal”.<sup>19</sup>

<sup>19</sup>Schwager (1996) is concerned with doing technical analysis for commodity futures contracts, not stocks. Following Edwards and Magee (1966, ch.16), it is ‘true’, in general, that techniques used in technical analysis of stocks and commodities are the same, as long as “proper allowance is made for intrinsic differences between commodity futures contracts and stocks and bonds”. Included in these differences are: the limited life of individual futures contracts; the presence in futures markets of commercial traders involved in hedging which renders near-term support and resistance levels less effective for futures; the need to interpret volume differently and to account for open interest; and, the greater importance of certain news events such as droughts or flooding. Given these qualifications: “Under what might be called normal market conditions, those chart patterns which reflect trend changes in the most simple and logical fashion work just as well



Fig. 6.7 Proctor and Gamble, 2004–2009.

While technical analysis thrives on the presence of trends, in many situations there is no discernable trend. In these situations, prices move in a “horizontal corridor that contains price fluctuations for an extended period” (Schwager 1996, p. 57) referred to as a *trading range* also known as a rectangle (Edwards and Magee 1966, ch. 9).<sup>20</sup> Following Poitras (2005,

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with commodities as with stocks”. However, Edwards and Magee make an important qualification to this statement: “successful speculation in commodities requires far more specialized knowledge, demands more constant daily and hourly attention. The ordinary individual can hope to attain a fair degree of success in investing in securities by devoting only his spare moments to charts, but he might better shun commodity speculation unless he is prepared to make a career of it”.

<sup>20</sup>The distinction between a ‘trading range’, a ‘rectangle’ and a ‘consolidation’ is not always clear. Following Edwards and Magee, a consolidation is a period of sideways movement in a trending market. Flags, pennants and wedges are consolidation formations, as are head-and-shoulders, scallops and saucers. Edwards and Magee (1966, p. 168) describe the rationale for consolidations: “An army that has pushed forward too rapidly, penetrated too far into enemy territory, suffered casualties and out-run its supplies, must halt eventually, perhaps retreat a bit to a more easily defended position and dig in, bring up replacements and establish a strong base from which later to launch a new attack. In the military parlance which we have all become more or less familiar these past few years, that process is known as *consolidating* one’s gains”. In other words, a consolidation is a ‘sidewise’ chart pattern composed of minor fluctuations that continues until the market has ‘caught up to itself’ and ‘is ready to go on again’. In contrast to

pp. 522, 523), Procter & Gamble (PG) is an example of a trading range stock (see Fig. 6.7). The 5-year price movement of PG is bounded above by \$75 and below by about \$50. Up-trends can stall out at the **resistance level** defined by the upper bound and down-trends can stall out at the **support level**, defined by the lower bound. A **breakout** occurs when prices penetrate either the resistance or support level. A breakout can be an important signal for securities with prices that have trading ranges. Once a breakout from a trading range has been established, the resistance level of the previous trading range becomes a support level for the next trading range. Determining whether a price chart represents a trading range or a trend is a key step in interpreting the chart. In the case of PG, the price did penetrate the support level during the market downdraft of February–March 2009 but soon rebounded back into the trading range. This illustrates the difficulty in identifying when a breakout has been confirmed. Most trading strategies used in technical analysis do not perform well in trading range markets. Those trading strategies that are designed to profit in trading range markets, such as oscillators, will tend to perform poorly in trending markets. Similarly, techniques for analyzing charts in trending markets, e.g., head-and-shoulders, flags and gaps, have little meaning in trading range markets.

There are practical difficulties in identifying and interpreting the support and resistance levels for a trading range. One difficulty involves the appropriate length of time to use in **defining a trading range**. As with the drawing of trend lines, changing the sampling interval will change the interpretation of the chart. Schwager observes that for a trading range to be established the horizontal corridor has to last at least a couple of months. Trading ranges can last for years. In such cases, it is often possible for the long-term trading range to be broken down into smaller trading ranges. In practice, breakouts from trading ranges are considered to be one of the most reliable technical indicators. Following Schwager (1996, p. 60), the **reliability of a breakout signal** depends on three factors: the duration of the trading range, the longer the duration of the trading range the stronger the signal; the narrowness of the trading range, the narrower the range the more reliable the signal; and, the ability of the breakout to meet criteria for confirmation, simply penetrating the support or resistance level is usually not sufficient to produce a trading signal. The use of breakout signals to trigger

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a consolidation, a 'rectangle' 'defines a contest between two groups of approximately equal strength... Nobody... can tell who is going to win until one line or the other is decisively broken'. In effect, a rectangle more-or-less defines a trading range.

trades has to be considered in the light of ‘the most important rule in chart analysis’. Schwager (1996, p. 180) describes this **‘failed signal’ rule**: “A failed signal is among the most reliable of all chart signals. When a market fails to follow through in the direction of a chart signal, it very strongly suggests the possibility of a significant move in the opposite direction”. Was this the case with the February–March 2009 failed signal in Fig. 6.7?

All this may seem confusing to the uninitiated. A breakout is a strong trading signal unless the breakout provides a failed signal in which case it provides a strong signal of a move in the opposite direction. This is compounded by the difficulty that arises with interpreting when a breakout has occurred. It is apparent that when a chart pattern has a breakout from a trading range through a resistance (support) level this is a buy (sell) signal. However, as Schwager (1996, pp. 67–69) observes:

It should be emphasized that a prior high does not imply that subsequent rallies will fail *at or below* that point, but rather that resistance can be anticipated in the *general vicinity* of that point. Similarly, a prior low does not imply that subsequent declines will hold *at or above* that point, but rather that support can be anticipated in the *general vicinity* of that point. Some practitioners of technical analysis treat prior highs and lows as points endowed with sacrosanct significance. If a prior high was 1078, then they consider 1078 to be major resistance, and if, for example, the market rallies to 1085, they consider resistance to be broken. This is nonsense.

Schwager recommends that there be a stronger confirmation signal than simply trading above (below) the resistance (support) level, such as having some minimum number of closes above (below) the resistance (support) level or being above (below) the resistance (support) level by some percentage amount or both. Many technical analysts that evaluate stock charts emphasize the importance of **high volume** as a prerequisite confirmation signal for breakouts and reversals. There are no hard-and-fast rules on breakout confirmation. This is part of the art in technical analysis.

The exercise reflected in Fig. 6.7 and the discussion of trends and trading ranges captures the significance of the following statement (Edwards and Magee 1966, p. 48): “the first and most important task of the technical chart analyst is to learn to know the important reversal formations and to judge what they may signify in terms of trading opportunities”. The number and variety of these **chart formations** is unsettling: the head-and-shoulders and the necktie breakout; flags, pennants and wedges; scallops and saucers; gaps, spikes and islands; triangle tops (bottoms) and

rounded bottoms (tops); and, V tops and bottoms. Interpretation of the various chart formations depends on the initial determination of whether the price chart is in a trend or trading range. For example, flags and pennants represent *continuation* signals in a major trend. These patterns are sideways price formations that are associated with a pause in a major trend. Triangles are a more complicated version of a continuation signal. Head-and-shoulders, double tops and bottoms and islands surrounded by gaps are indicators of reversals. Combine this with the difficulties of determining whether the price chart reflects a trend or trading range and the conclusion of Schwager (1996, p. 147) is understandable: “chart analysis remains a highly individualistic approach, with success or failure critically dependent on the trader’s skill and experience”.

### *Moving Average Techniques*

Breakouts, trading ranges, chart formations and the like are concepts that apply to the basic charts. Even the staunchest believer in technical analysis will acknowledge that the interpretation of chart patterns is complicated by the noisy character of prices. The drawing of lines on charts is a subjective process, at best. In order to remove some of the noisiness in prices, it is a natural development to consider further processing of the price data before plotting the information on a chart. Going back at least to Gartley (1930, 1934), technical analysts have explored the use of *moving average techniques* in order to smooth the time series of prices. Over time, more complicated processing of price data, such as oscillators and stochastics, have been introduced. Moving averages have the attractive property that the unit of measurement is the same as for prices, something that is not always true of more complicated processing procedures. As a consequence, moving averages can be plotted onto the price charts and used to aid in assessing the chart patterns. Because moving averages smooth the price data, conventional chart formations such as flags and pennants will not be apparent in the moving average.

A moving average can take a variety of forms. The common element in the different forms is the use of a *fixed sampling window*. There is always a fixed number of observations used to calculate the moving average value for any given day. An  $T$ -day moving average uses the current price and the most recent  $T - 1$  past prices to calculate the average at a given time  $t$ . As time moves forward, the most recent observation is added and the most distant observation is dropped, maintaining  $T$  observations in the average calculation. In particular the simple and weighted  $T$  day moving



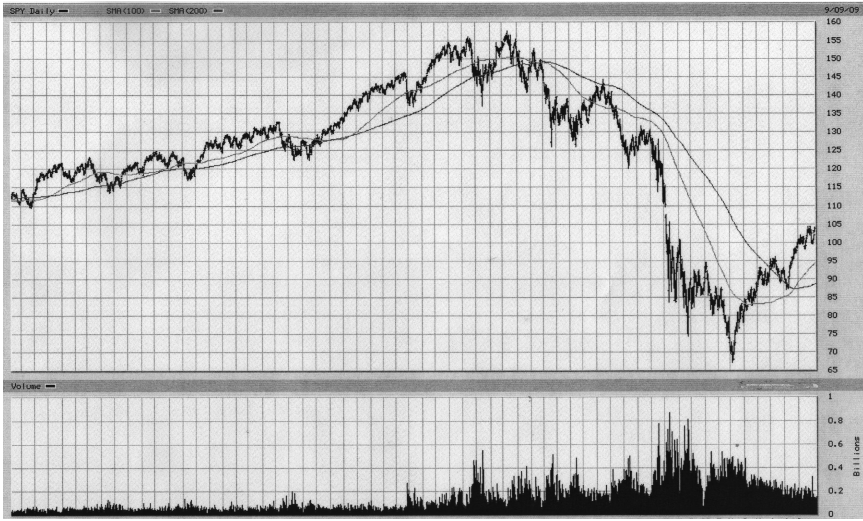


Fig. 6.8 200-day vs. 100-day simple MA chart for SPY, 2004–2009.

averages at time  $t$  are calculated as

$$\text{Simple MA : } \bar{P}(t, T) = \frac{\sum_{i=0}^{T-1} P(t-i)}{T}$$

$$\text{Weighted MA : } \bar{P}(t, T)^W = \sum_{i=0}^{T-1} w(i) P(t-i)$$

where  $\bar{P}(t, T)$  is the time  $t$  value of the simple moving average and  $\bar{P}(t, T)^W$  is the time  $t$  value of the weighted moving average where the sum of the  $w_i$  ( $\geq 0$ ) weights is required to be equal to one. The simple moving average weights each of the observations equally ( $1/T$ ) (see Fig. 6.8). Variations of the weighted moving average approach, such as the exponential moving average, use different weighting schemes. A 1-day moving average is the original price chart. The simple  $T$  day moving average is a special case of a weighted moving average where  $w_i = 1/T$ . Selecting the appropriate length for a moving average is a subject of considerable debate and study by technical analysts, e.g., Kaufman (1978, pp. 83–85).

A number of different estimators are available in addition to the simple equally weighted moving average. A popular alternative is the exponentially weighted moving average (EMA) that has the form:

$$EMA(t) = \alpha P(t) + (1 - \alpha) EMA(t-1)$$

where  $0 < \alpha < 1$ . Expressing in lag operator form, manipulating and solving for  $EMA(t)$ , it follows that the  $EMA$  can be expressed as a infinite weighted moving average with weights  $w_i = \alpha(1 - \alpha)^i$ . More precisely:

$$EMA(t) = \alpha P(t) + \alpha(1 - \alpha) P(t - 1) + \alpha(1 - \alpha)^2 P(t - 2) \\ + \alpha(1 - \alpha)^3 P(t - 3) + \dots$$

In various sources, e.g., Schwager (1996, p. 602), it is stated that the  $EMA$  “corresponds roughly to a simple moving average” with length  $T$  where:  $\alpha = 2/(T+1)$  or  $T = (2 - \alpha)/\alpha$ . However, this condition only follows under certain conditions.

### *Moving Average Patterns*

Depending on the objectives of the technical analyst, moving averages can be used to identify trends, generate trading signals or both. Conventional wisdom recognizes a moving average (MA) as a trend following procedure. In trading range markets, which are often the case, moving averages will not typically be a useful tool. Because a moving average takes into account both current and lagged values of prices, the relationship between the observed price series and the MA, or between moving averages of different lengths, can be used to identify the trend. Due to the lagging nature of an MA, in a rising market the moving average value for a given date will lie below the price, or a moving average with a shorter length, for that date. Conversely, in a declining market the MA will lie above the current price (see Figs. 6.8 and 6.9). Trend reversals, ***crossovers***, occur when the sequence of current prices crosses the moving average, or a shorter MA crosses a longer MA. The transition from an uptrend to a downtrend occurs when the price series penetrates the moving average from above and vice versa for a downtrend to an uptrend. These crossovers are trading signals. In some cases, the moving average is compared with the original price series, in other cases a moving average of one length is compared with a moving average of another length. In Fig. 6.8, trading signals can be generated by comparing the 200-day moving average with 100-day moving average or comparing either with the raw price chart.<sup>21</sup>

One difficulty of using a moving average to identify a trend or generate a trading signal is that, by construction, the moving average will lag the

<sup>21</sup>The use of two moving averages of different lengths to generate trading signals is a basic type of oscillator system, e.g., Schwager (1996, p. 524). Such systems are usually referred to as ‘dual moving average’ or DMA systems.

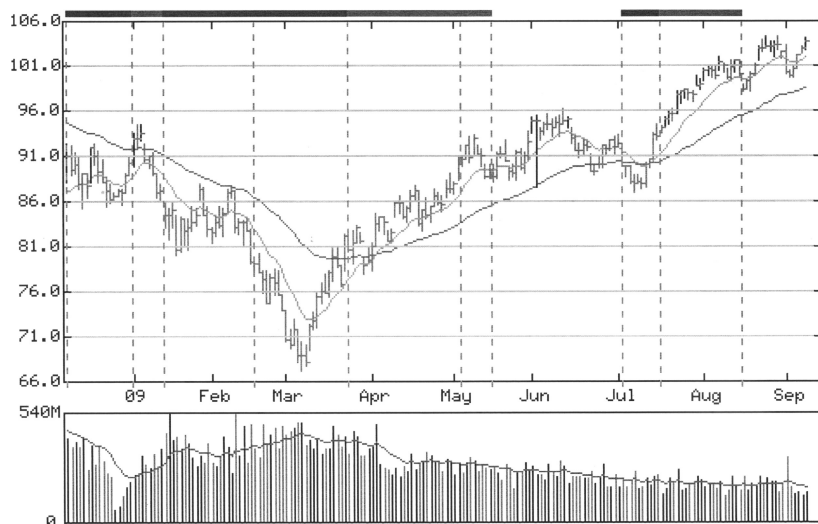


Fig. 6.9 50-day vs. 13-day Exponential MA chart for SPY, 09/08-09/09.

actual price series. The longer the moving average, the longer is this lag, e.g., a  $T$  day moving average will have a shorter lag than a  $T + N$  day moving average. Examining the 200-day moving average in Fig. 6.8, it is apparent that the S&P peaked in October 2007 while the 100-day MA crosses the 200-day MA from above — a strong bearish signal — in Jan 2008. The bullish signal of the 100-day MA crossing the 200-day from below appears in July 2009. The use of the actual price series or short moving averages to determine crossovers raises the possibility of *whipsaws* where the price series crosses the moving average in one direction only to reverse course shortly thereafter and cross in the other direction. This is apparent in Fig. 6.10 in the period prior to October 2007 when the price series is used to identify crossovers. The failings of the moving average in a trading range market are apparent in Fig. 6.10 which provides results for 100- and 200-day moving averages for Procter and Gamble over a ten year sample period.

Finally, while the preceding discussion focused on price charts, the scope of technical analysis does include a much broader set of variables. Charting, moving averages, momentum, oscillators and the like apply to this broader set of variables in much the same fashion as with prices. For example, some technicians actively monitor a *breadth indicator* to get a sense of underlying market demand and the general near-term or long-term direction of the market. Technical indicators for market breadth involve calculations

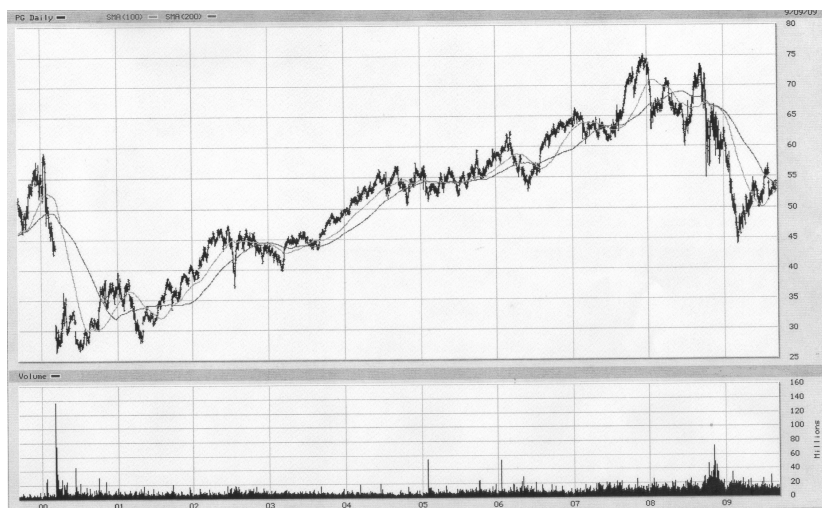


Fig. 6.10 200-day vs 100-day sample MA chart for PG, 1999–2009.

with advancing and declining issues, sometimes supplemented by volume. Included in these indicators are: the advance–decline line; advance–decline ratio; absolute breadth index; breadth thrust; McClellan oscillator; and the summation index (see [www.marketscreen.com](http://www.marketscreen.com)). Perhaps the mostly widely followed technical indicator of breadth is the advance–decline line — the cumulative, ongoing sum of the difference between the number of stocks closing higher minus the number of stocks closing lower each trading day. Alternatively, there is the advance decline ratio — the ratio of advancing issues to declining issues.<sup>22</sup> The daily difference between the number of advancing and declining issues (not cumulated) is typically evaluated as a momentum indicator.

The typical intuition used to assess a breadth indicator is based on the presumption that the direction of the major market averages tends to persist at trend reversal points. Market averages such as the 30 stock DJIA or the value weighted S&P 500 give disproportionate emphasis to a narrow group of stocks. This leads to the following interpretation of, say, the advance–decline ratio: at market peaks (troughs), the narrowly based

<sup>22</sup>The rise in the importance of breadth indicators is a relatively recent phenomenon. Edwards and Magee (1966), for example, do not examine breadth indicators. One example is the ‘breadth thrust’ indicator developed by Martin Zweig, a frequent guest on the once popular PBS program *Wall Street Week* with L. Rukeyser.

DJIA will continue to increase (decrease) while market breadth declines (increases). In other words, a divergence in the advance–decline ratio and the DJIA is a signal of a change in market trend. Due to the day-to-day variation in the breadth indicator (and the DJIA), moving average methods can be used to smooth the series to give a better representation. Similarly, the market breadth indicator can be examined in isolation and used as a trend indicator. As with price charts, when the short-term, say 10-day, moving average of the breadth measure cuts the long-term, say 200 day, moving average from below (above) this is a signal for an upward (downward) movement in prices. In addition to changes in market trend, breadth indicators such as the McClellan oscillator can also be used to assess direction within trading range markets.

#### **6.2.4 *Contrarian and Contrary Opinion Strategies***

Like ‘value’ and ‘growth’ stocks, the ‘contrarian approach’ to equity security analysis is a source of semantic confusion. The terminology ‘contrarian’, ‘contrarian strategy’ or ‘contrarian approach’ can apply to a wide range of strategies involving different measures, applicable in a variety of different situations. The basic motivation of the contrarian strategy is to trade in the opposite direction of the trend in prices or market sentiment. Differences in definition arise from the theoretical rationale used to motivate the contrarian strategy. In modern Finance, the ‘contrarian’ approach is often equated with ‘value investing’. For example, Levis and Liodakis (2001) claim: “The profitability of contrarian investment strategies is now one of the most well known empirical facts in the finance literature” where ‘contrarian’ refers “to various strategies based on buying/selling stocks that are low/high relative to three accounting measures of performance — earnings, cash flows, and book values — as well as strategies based on low/high EPS growth”. This claim of ‘most well known empirical fact’ is supported by references to a number of studies, including Fama and French (1998). Yet, Levis and Liodakis also proceed to observe that: “the outperformance of such strategies has declined and even reversed in the most recent years”.

The process of presenting ‘strong empirical evidence’ that is later refuted is becoming a characteristic feature of modern Finance. This unsettling feature is compounded by another confusing feature: the tendency to redefine words that have an established but different meaning in either the vernacular or old finance usage. From the efficient markets hypothesis — where ‘technical analysis’ and ‘fundamental analysis’ are given interpretations that do not do justice to those approaches — to ‘contrarian’ investment

strategies — where the emphasis is placed on the use of accounting measures to select stocks — modern Finance has taken an exclusionary attitude regarding previous approaches to the subject. Redefining words that already have established alternative meanings — such as ‘contrarian’ investment strategy — shows either ignorance of the internal workings for other approaches to Finance or a disappointing lack of respect for these approaches.<sup>23</sup> It is not even clear that the use of ‘contrarian’ is grammatically correct. The connection between the use of accounting measures and a contrarian outcome depends on an empirical assumption that, say, high (low)  $P/E$  or  $P/BV$  stocks are past winners (losers), e.g., Lakonishok *et al.* (1994). Only if the strategy involves buying losers and selling winners can the approach be interpreted as contrarian, and even then the meaning is substantively different than used in other contexts.

The confusion created by the definition of ‘the contrarian approach’ used in modern Finance is unfortunate because the long history of the contrarian approach contains many insights. The basis of this approach to equity security valuation is reflected, for example, by Keynes (1936, p. 155): “the professional investor is forced to concern himself with the anticipation of impending changes, in the news or in the atmosphere, of the kind by which experience shows that the mass psychology of the market is most influenced”. In effect, prices in equity security markets are the outcome of ‘crowd psychology’ or ‘mass psychology’. As Neill (1954, p. 5) observes: “What it comes down to in the final analysis is that a ‘crowd’ thinks with its heart (this is, is influenced by emotions) while an individual thinks with his brain”. Keynes (1936, p. 154) provides more substance for this observation: “A conventional valuation which is established as the outcome of the mass psychology of a large number of ignorant individuals is liable to change violently as the result of a sudden fluctuation of opinion due to factors which do not really make much difference to the prospective yield; since there will be no strong roots of conviction to hold it steady”. The

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<sup>23</sup>Siegel (1998, ch. 5) is an exception. Siegel provides a brief discussion of Neill (1954) and overviews empirical evidence on a study of investor sentiment as captured in the indicator published by the investment advisory service Investor’s Intelligence. This indicator is based on sentiment scoring of a large sample of market newsletters. Over a 35-year sample, the indicator was found to have ‘strong predictive power’. However, Siegel (1998, p. 65) does contribute to the semantic confusion about ‘value investing’ as a contrarian strategy: “Value investors are contrarians who believe that swings of optimism and pessimism about the market and individual stocks are frequently unjustified, so buying out of favor stocks is a winning strategy”.

contrarian attempts to be ahead of the crowd by identifying when mass psychology has driven prices too far in one direction.

Though the basis of the contrarian approach can be traced back to early writings on security markets, e.g., de la Vega (1688), the development of an organized approach aimed at trading securities did not occur until the 1950s. A well developed association of contrary opinion with technical analysis can be traced to Drew (1951) where the views of *Humphrey Neill* were recognized. Neill (1954, p. 15) appraises the state of the subject in the mid-1950s:

The Theory of Contrary Opinion is not something that one reads about in books or histories. There is no literature on the subject. Nothing has been written directly on the use of contrary opinion that I am aware of, except an excellent chapter pertaining to “contrary *market* opinion” in [Drew 1951].

Neill had been developing and writing about contrary opinion since the 1920's, mostly in newspaper columns and an investment advisory newsletter, *Neill Letters of Contrary Opinion*. A driving concern for Neill's inquiries was the question: why is the public so often wrong? Neill sought the explanation for this question in the role of ‘human nature in finance’, more specifically on the role of mass psychology and the actions of individuals in crowds.

For Neill the ‘*art of contrary thinking*’ applies to a wide range of issues — political, social and economic: “The art of contrary thinking consists in training your mind to ruminate in directions opposite to general public opinions; but weigh your conclusions in light of current events and current manifestations of human behavior”. Though Neill has insights into various realms of human activity, it is the implications of contrary thinking for technical analysis that has received the greatest recognition (Neill 1954, p. 16):

One can interpret charts almost any way he wishes. He can read into their ‘formations’ just about any probable result he hopes for. Which is to say, that if one is bullish at heart, his chart reading is likely to be interpreted optimistically; if bearishly inclined, charts accomodatingly will “say” that the market is going down. During one-way market trends (whether up or down) the trends are clearly enough defined on the charts; but when the market comes to an impasse and everybody is in a quandary as to the direction prices are likely to go, then the charts, too, are usually “silent”.

It is in these periods of indecision in the charts that “each person would interpret ‘technical action’ in accordance with his deep-seated personal

opinions”. Wishful thinking takes over and the “inherent traits of hope, greed, pride-of-opinion, and similar human feelings” bias the analysis and contribute to making “successful speculation one of the most difficult arts to master”.

For Neill (1954, pp. 44–46), the theory of contrary thinking is ‘intangible’, it is a habitual approach to examining the world. The public, the crowd is *not* wrong all the time. “The public is perhaps right more of the time than not. In stock market parlance, the public is right *during* the trends but wrong at both ends!” In other words, the public is ‘wrong when it pays the most to be right’. Neill recognizes that “when we adopt a contrary opinion, as a guide, we must recognize that we may be *too far* ahead of the crowd”. This is because events are often slow to change. Weeks or months may pass before a trend changes and the contrary opinion proves to be correct. However, as “there is *no* known method of *timing* events or trends... it is wiser to be early than to be late — in most economic decisions”. Neill makes the convincing point, based on years of heuristic inductive analysis, that consideration of contrary opinion improves forecasting ability: “Contrary thinking unquestionably helps one to avoid many common errors in forecasting — errors arising from miscalculating what the public will do”. If anything, the art of contrary thinking will alert the individual to the bombardment of self-serving information and news that is dispensed from brokerage houses, government departments and agencies, and the popular financial media.

Making the theory of contrary thinking operational requires some method of measuring the sentiment of the ‘crowd’. Since Neill, considerable effort has been dedicated to this task. In the absence of well-developed or acceptable measures, Neill (1954, p. 22) observes:

you will have to peruse a pile of news and comments. However, our radios, and magazines unload such a flood of economic news and propaganda these days, it is not difficult to get a fairly accurate cross section of what people probably are thinking about and what the composite opinion is likely to be. Also — and this is important — of what some groups *want* us to accept and believe.

Neill identified official economic releases as another possible source for market sentiment, because of the weight such opinions have on the public. At Neill’s time, the Council of Economic Advisors had an impact similar to what the Board of Governors would have at present. Neill also provides an important cue for later developments in the measurement of sentiment: “A consensus of businessmen — or brokers — is valuable in making an



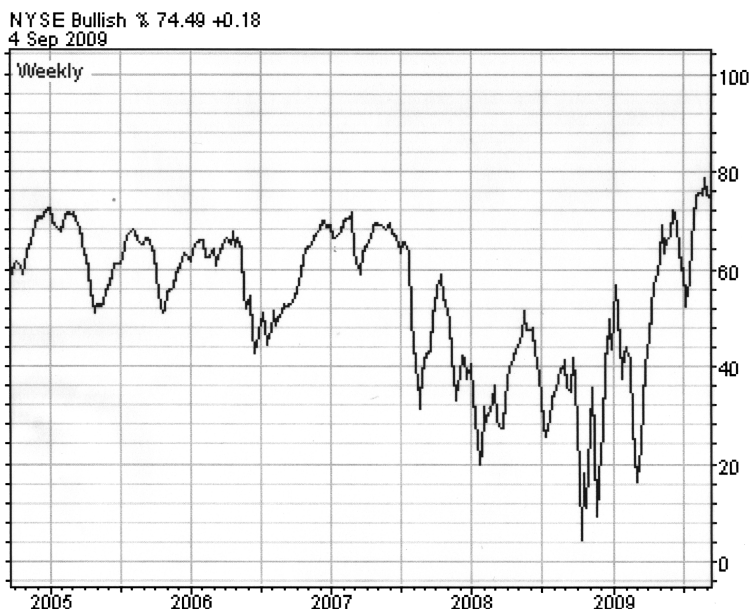


Fig. 6.11 Investor's intelligence investment advisory indicator.

analysis of opinions 'to be opposite to' because of their influence on general sentiment". An example of how this notion has been made operational is provided by the Investor's Intelligence investment advisory service ([www.investorsintelligence.com](http://www.investorsintelligence.com)) that calculates a number of contrary opinion indicators based on surveys of market sentiment expressed: in investment advisory newsletters, e.g., Siegel (1998, p. 87) and by NYSE members (see Fig. 6.11).

In addition to surveys of investment advisory newsletters, opinions of floor traders and brokerage house recommendations, Siegel (1998, p. 89) makes reference to a "sentiment indicator based on the recommended portfolio allocations of market analysts and portfolio managers. Whenever their recommended allocation to stocks falls below 50%, indicating a high level of pessimism about the market's prospects, subsequent returns have been high". Siegel claims that the Director of Quantitative and Equity Research at Merrill Lynch "calls this his single most powerful quantitative market-timing barometer". Like any mechanical investment strategy, there is the possibility that the feedback effect will undermine the effectiveness of such a contrarian strategy. However, *measures based on surveys and analysis of newsletters* have a number of features that would mitigate the

feedback effect: the information is not widely disseminated and, in some cases, the measures are proprietary; being based on surveys and the like, the measures change slowly over time; and, the interpretation of the measure is subjective. It is arguable whether such contrarian measures are not more within the realm of fundamental analysis than technical analysis.

In considering the performance of contrary opinion and other contrarian indicators, *the forecasting horizon* is a key variable. Based on the limited evidence that is available, it appears that contrary opinion indicators have been effective for determining turning points in long-term trends. However, the use of contrarian indicators for purposes of short-term speculation — the main battlefield of technical analysis — is likely to be less effective, if only because contrarian indicators tend to have a long-term focus. In order to be used for short-term trading, the contrarian measures need to be based on information sets that change on a regular basis. This runs the risk of altering the conceptual foundation upon which the contrarian approach is based. Some indicators that have been suggested in the past that could be used for short-term trading, such as the ratio of purchases to sales for odd-lot transactions (Kaish 1969) or mutual fund cash positions (Massey 1979), also seem to work best (if at all) for predicting long-term turning points. In an odd twist, the ‘buying losers and selling winners’ contrarian strategy suggested by modern Finance adherents seems to be the closest that a profitable ‘contrarian’ strategy comes to a short-term horizon.

## 6.3 Recent Developments in Technical Modeling

### 6.3.1 *Relative Strength*

The epistemology of economic positivism requires, where possible, that theoretical valuation models be empirically tested on observed data. Knowledge is conceived to progress linearly as more precise empirical observations are obtained and theoretical hypotheses are developed that have better predictive power. In the process of empirical testing and observation, insights are gained inductively that permit the development of theoretical models with a better fit to reality.<sup>24</sup> This intellectual process has produced

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<sup>24</sup>In practice, the process of producing theoretical models is guided by ‘stylized facts’ that have been identified in previous examinations of the data. This process of developing theoretical models from previously known empirical results and then testing those models as though there was no prior knowledge of the data has been explored by Leamer (1978). The progress of knowledge in economics and finance has been characterized by a variety of ‘specification searches’ that are explored by Leamer.

enormous strides in the natural sciences, where an immutable physical reality is the object of analysis. The gains achieved have been more debatable in the human sciences where the exercise of free will by individuals undermines the assumption that the objective reality is immutable. In contrast to modern Finance, the bulk of technical analysis proceeds solely by empirical observation. As such, the ‘science of technical analysis’ (Edwards and Magee 1966, p. 6) is still subject to the general criticism aimed at modern Finance, i.e., that objective reality in the human sciences is not immutable. The assumption that chart patterns repeat over time requires a degree of predictability for human behavior that is difficult to reconcile with the exercise of free will and the evolution of the social and historical context.

In any event, technical analysis is predicated on the assumption that ‘history repeats itself’. The subject is ‘forward looking’ in the sense that the reasons why history repeats are of relatively little interest compared to the identification of ‘repeatable patterns’ that permit prediction of future price movements. Induction drives the method of analysis. A range of these repeatable patterns includes the various types of chart patterns and associated moving average techniques. These methods of technical analysis can be characterized as traditional, in the sense that the information of interest can be presented on a single price chart. Over time, technical analysis has evolved methods of analysis that are more sophisticated, in the sense that the information of interest is mapped from the price chart to another chart, or from two price charts onto another chart. Included in these more sophisticated methods are indicators of relative strength, momentum and oscillation. These indicators involve evaluating functions of the original price series. In keeping with the conventional approach of technical analysis, the charts of these more sophisticated indicators are usually used as the method of evaluation, though this is not necessary.

The indicators of relative strength, momentum and oscillation are closely related. In some presentations, relative strength and price momentum are used synonymously, e.g., Macedo (1995), though there are good reasons to make a distinction between the concepts. In an odd semantical twist, Wilder (1978) even introduced a form of oscillator referred to as the ‘Relative Strength Index’. In what follows, relative strength is interpreted in the traditional sense of Levy (1967, 1968) and others, e.g., Bohan (1981). To avoid potential semantic confusions, some sources refer to the traditional relative strength concept as *comparative relative strength*, e.g., [www.marketscreen.com](http://www.marketscreen.com). Using the traditional definition,

(comparative) relative strength is an extension of the basic notion in technical analysis that prices move in trends. The relative strength extension postulates that relative performance will also follow trends. Stocks or industries that are outperforming will continue to outperform until the trend is reversed. For stocks, this out-performance can be measured relative to the market average or to other stocks in the same industry or to some other stock or whatever. For industries, out-performance is measured relative to the market average or to other industries.

Relative strength is a widely used concept that can be measured in various ways. The simplest measure — plotting of the relevant price series on a close-only chart — is widely available from most on-line charting sites. For example, Fig. 6.12 compares the relative strength of the S&P 500 and NASDAQ stock indexes using a one-year close-only chart of percentage price changes. For many applications, this assessment of relative strength is sufficient. Analysts requiring more precise information can calculate indicators from the price series. A simple example of such a relative strength indicator would be the ratio of a given stock’s price to, say, the S&P 500. If this ratio increases over time, then the stock has relative strength compared to the index. However, the scale of this measure would not be directly comparable to the ratio indicator value for another stock relative to the S&P. While it is possible to plot these individual ratio series and use chart analysis

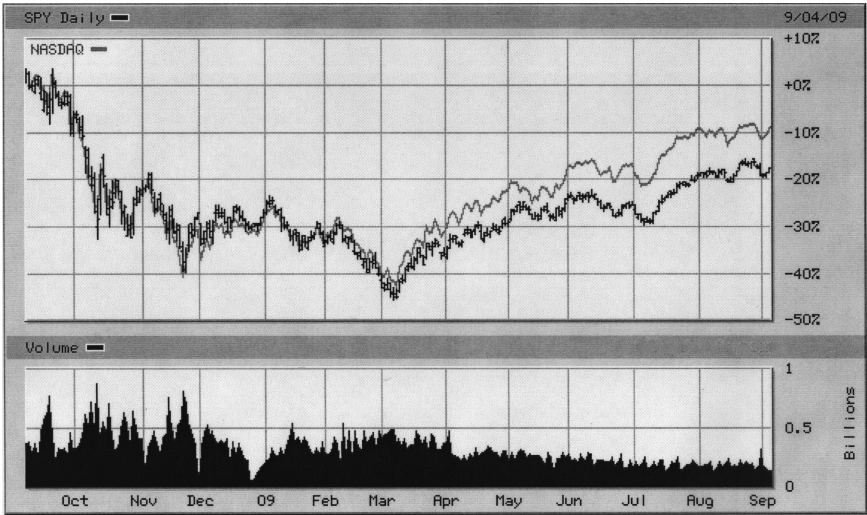


Fig. 6.12 One-year comparative relative strength of S&P 500 and NASDAQ, 9/08-9/09.

techniques to identify trends, trading ranges, breakouts and so on, direct comparison of indicators across stocks is not feasible due to the absence of scale comparability. This can be corrected by scaling the indicator relative to some base period and multiplying by 100 to create an index number. The base year could be selected to correspond to, say, the last major reversal in the sector or the market.

Relative strength is somewhat different from most other technical indicators because it deals with the “co-movement” of prices. Even if successive price changes are serially uncorrelated, there may still be exploitable information in the co-movements. As Levy (1967) observes: “The intercorrelation or co-movement of stock prices could conceal existing dependencies in successive price changes”. For example, unlike momentum that measures directional change, *relative strength can increase in both up markets and down markets*. Consider the relative strength of a stock measured using the ratio of the stock’s price to the S&P 500. Both the price and the market average could be falling at the same time that the measure of relative strength is increasing. Typically, it is assumed that if, say, a given stock is outperforming the market, then this relative strength can also be expected to follow a trend. Using the tools of technical analysis, these trends can be identified. As long as the relative strength trend is unbroken, stocks that are strong in bear markets can be expected to outperform when the primary trend changes to a bull market. This co-movement of stocks with market averages, between stocks, between industries and so on can be examined using a range of tools from technical analysis. Levy (1967), for example, suggests the uses of ‘divergence ranks’ and ‘market ranks’.

Despite holding considerable promise, there has been little interest in relative strength indicators in recent years. One possible reason for this is the emergence of the CAPM as an analytical tool. By construction, the market model representation of the CAPM provides two parameter estimates for a security: the alpha and the beta. The information provided by these parameter estimates is a statistically sophisticated form of relative strength analysis. When expressed in excess return form, the beta measures the co-movement of the security return with the market return and the alpha measures the excess (deficit) return after adjusting the security return for equilibrium systematic risk compensation. In effect, the alpha of a security is a measure of relative strength, adjusted for systematic risk. As such, the use of alpha addresses concerns expressed in Levy (1967, pp. 609, 610) and other early studies of relative strength indicators about ‘the riskiness of the various technical indicators’. While useful, the temporal instability in the parameter estimates of the market model leaves room for improvement

in the use of alpha as a relative strength indicator. Perhaps the use of charting techniques, moving averages and so on can be used to improve the usefulness of the market model?

### 6.3.2 *Momentum and ‘Price Rate of Change’*

It was observed that the development of technical analysis involved a gradual increase in the sophistication of techniques associated with the processing of price information. At least since Schabacker (1930), it has been recognized that, in order to deal with the noisiness of the raw price series, moving averages can be calculated. The values of a moving average are smoother than the price series and can be plotted directly on the price chart. The smoothing of the price information in this fashion alters basic chart patterns such as head-and-shoulders, flags and pennants that are the basic tools of chart analysis involving unprocessed prices. This leads to different trading rules for moving averages. Eventually, processing of price information had to achieve a level of sophistication where the resulting indicators could not be plotted directly on the price chart.<sup>25</sup> Another chart or series of charts has to be prepared in addition to the basic price chart. (This use of additional charts in technical analysis was already the case with volume information that cannot be plotted directly on the price chart.) Much like a moving average, the objective is to calculate some function of the underlying price series and use that to identify trends, determine trading signals or both. Because of the large number of potential functions that could be applied, the scope for these types of extensions to technical analysis is almost limitless.

Precisely when momentum entered the lexicon of technicians is unclear.<sup>26</sup> It is only in the last three decades that considerable attention from both practitioners and academics has focused on the concept. As with so many concepts in Finance, there is divergence both between

<sup>25</sup>Included in the more sophisticated group of technical indicators are techniques with appealing names such as Elliot waves, Bollinger bands, Moving Average Convergence-Divergence (MACD), Lane Stochastics, and Double-Smoothed Stochastics, e.g., Blau (1995).

<sup>26</sup>Bierovic (1996, ch. 15 in Schwager 1996) observes that: “As early as the 1920s, technical analysts were creating oscillators to measure a market’s momentum rather than limiting their efforts to determining the market’s trend”. However, no references are given. It is likely that Bierovic is referring to the introduction of ‘dual moving average’ techniques. Recognizing that the more general term ‘oscillator’ includes momentum as a special case, the logic of momentum analysis does have a long history.

the vernacular and the academic definitions of ‘momentum’. For many practitioners, e.g., Schwager (1996), Blau (1995), and Kaufman (1978), **momentum** is defined as the rate of change of prices over a period of time. More precisely, the  $k$  day momentum indicator,  $M(t, k)$ , is defined as  $M(t, k) = P(t) - P(t - k)$ , where  $P$  is the closing price. The  $k$  day *price rate of change*,  $ROC(t, k)$ , is defined as  $ROC(t, k) = P(t)/P(t - k)$  (or in percentage change terms  $ROC(t, k) = \{(P(t) - P(t - k))/P(t - k)\}100$ ). Other practitioners, e.g., [www.marketscreen.com](http://www.marketscreen.com), define momentum as the ratio of prices  $k$  days apart and the price rate of change as the first difference or percentage change in prices. It is also possible to define momentum using other variables than closing prices. For example, a moving average of prices can be used for a momentum indicator calculated by taking the difference of the moving average values  $k$  days apart. It is also possible to take a moving average of the momentum value. However, if only because of the differing interpretation of the momentum chart patterns, it is more appropriate to refer to these more involved momentum measures using different terminology.

Whatever the definition, the basic intuition of momentum relates to the slope of the price chart. For purposes of illustration, consider a smooth non-linear function that starts at zero and increases monotonically to a maximum. (The cumulative normal distribution function is a practical example of such a function with the normal density function as the representation of the slope of that function.) Basic calculus provides the result that the slope of the function will initially increase and then start decreasing until the slope reaches zero when the function reaches a maximum. As such, the slope of the function signals a maximum prior to the maximum being reached; it follows that the momentum chart can theoretically provide a signal for a change from uptrend to downtrend. The momentum function will achieve a maximum prior to the price function, crossing zero when the price function maximum is achieved. A similar analysis applies for a minimum. This basic intuition of selling (buying) at the maximum (minimum) of the momentum function is complicated by the noisy fluctuations of market prices. Consider the simple case of the one-day momentum,  $\{M(t, 1)\}$ . Consistent with being a price difference, it is usually the case that the one-day momentum chart is not a smooth function, crossing the zero line numerous times over the time period, making the momentum signal difficult to evaluate.

The difficulty interpreting the momentum function is usually approached by using larger differencing intervals to define momentum. For example, Poitras (2005, pp. 542, 543) uses momentum charts for  $\{M(t, 3)\}$ ,  $\{M(t, 9)\}$  and  $\{M(t, 20)\}$  to demonstrate that, while still erratic, as the

differencing interval is increased the momentum function becomes less erratic such that the *ex post* maximum and minimum values become easier to identify. The longer 20-day differencing interval does not have as many values in the extreme ranges. Recognizing that momentum can be interpreted as an oscillator, the maximum and minimum ranges can be used to define ‘overbought’ and ‘oversold’ levels that, in turn, can be used to specify trading signals. The use of specific differencing intervals is much like the choice of a sample length for a moving average, 100- and 200-day  $\{M(t, 100)\}$  and  $\{M(t, 200)\}$  momentum charts may have desirable properties. Selection of a specific differencing interval or comparison across a range of intervals are considerations that a technical analyst has to consider when constructing a trading system based on momentum indicators. Unfortunately, few on-line charting services provide the ability to change the default differencing interval.

In considering momentum and moving average indicator, there are theoretical relationships among the indications that need to be recognized. In particular, observing that momentum and the simple  $T$  day moving average  $\bar{P}(t, T)$  are defined as

$$M(t, k) = P(t) - P(t - k) \quad \bar{P}(t, T) = \sum_{i=0}^{T-1} \frac{P(t - i)}{T}$$

Setting  $k = T$  it is possible to specify the relationship between the momentum and moving average indicators. For example, consider the case where  $k = 5$ . In this case  $M(t, 5) = P(t) - P(t - 5)$ . Similarly,  $\bar{P}(t, T) = \{P(t) + P(t - 1) + P(t - 2) + P(t - 3) + P(t - 4)\}/5$ . But  $\bar{P}(t, T) = \bar{P}(t - 1, T) + \{[P(t) - P(t - 5)]/5\}$  and it follows that  $M(t, 5) = \{\bar{P}(t, T) - \bar{P}(t - 1, T)\}5$ . More precisely, it is possible to show in general that for  $k = T$ :

$$M(t, T) = \{\bar{P}(t, T) - \bar{P}(t - 1, T)\}k$$

This result can be used to establish a relationship between a momentum oscillator and a dual moving average oscillator.<sup>27</sup> On the interpretation of this connection between moving averages and momentum, Blau (1995, p. 13) makes the following statement:

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<sup>27</sup>It is possible to use moving average techniques to smooth the momentum function. For this purposes, most technical analysts use exponential weighted moving averages (EMA), e.g., a 20-day EMA of  $M(t, 1)$ . In some cases, e.g., Blau (1995), an EMA of different length is taken of the EMA resulting in, say, a 5-day EMA of the 20-day EMA of 1-day momentum. This process is called ‘double smoothing’.



Moving averages performed on prices introduce a lag. The longer the duration of the moving average, the greater is the lag. A 300-day moving average, for example, produces a tremendous amount of lag. *A single moving average performed on the momentum of price behaves in an altogether different manner. By contrast, the longer the duration of the moving average on momentum, the lower is the lag.* A 300-day moving average, for example, approximates a zero-lag situation. With emphasis, again: *A large moving average on momentum produces low lag price determination.*

In the limit: “large moving averages of momentum... have, in the limit, the exact *shape* of price” (Blau 1995, p. 14).

In contrast to the wide diversity of definitions and interpretations associated with momentum that are used by practitioners, academic studies of momentum use a relatively simple approach to definition and interpretation. Consider the ‘momentum’ strategy used by Jegadeesh and Titman (2001, p. 703) for a sample of all NYSE, Amex and Nasdaq stocks over a 1965–1998 sample: “at the end of each month we rank the stocks in our sample period based on their past six-month returns... then group the stocks into 10 equally weighted portfolios based on these ranks. Each portfolio is then held for six months following the ranking month”. While based on the notion of buying stocks using  $M(t, 6 \text{ month})$ , the connection to the concept of momentum used by technical analysts is decidedly underdeveloped. This lack of correspondence is not surprising when it is recognized that Jegadeesh and Titman (1993, 2001), Guitierrez and Kelley (2008) and other academic Finance studies that have examined ‘momentum strategies’, e.g., Chan *et al.* (1996) and Chan *et al.* (2000), are not concerned with testing the profitability of technical analysis. Rather, the concern is with testing the hypothesis of ‘buying winners and selling losers’ that is suggested by the behavioral finance challenge to the modern Finance orthodoxy.<sup>28</sup>

A number of academic studies have demonstrated the potential profitability of momentum strategies. The momentum differencing interval

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<sup>28</sup>The general discussion of the rhetoric of Finance queried how much of the persuasion used in modern Finance is targeted at ‘conversations between academics’ that take place in selected academic journals. Jegadeesh and Titman (2001, p. 701) provides an interesting example of this discussion: “Because there are potentially large payoffs to any viable model that predicts stock returns (in terms of publications and/or money management revenues) many academics and practitioners have, no doubt, independently tested a wide variety of trading strategies”. Putting aside the questionable empirical validity of the statement, the connection between ‘large payoffs’ for academics and ‘publications’ (presumably in the appropriate journals) is difficult to avoid.

varies across studies, e.g., Jegadeesh and Titman use a six-month interval while Chan *et al.* examine five differencing intervals varying between one week and six months. In contrast to the practice in technical analysis where an individual security is usually examined, the academic studies focus on classification of a universe of stocks into portfolios. Though these academic momentum studies have been subjected to the criticism of ‘data-snooping bias’ by other studies, it is difficult to ignore the sharpness of the statistically significant results for the profitability of the simple momentum strategies. For example, for the full sample of stocks over three different sampling periods (1965–1998, 1965–1989, 1990–1998), Jegadeesh and Titman (2001, p. 704) report monthly returns that decline monotonically from a high of (1.65, 1.63, and 1.69) for the highest decile of equally weighted momentum portfolios down to the lowest decile portfolios (0.42, 0.46, and 0.30). The strength of these results has led to the emergence of a ‘stylized fact’ that investors ‘under-react’ to short period returns. Whether this stylized fact will withstand closer scrutiny is, at present, unclear.

### 6.3.3 *Oscillators and MACD*

The reference to an ‘oscillator’ is inherited from physics where the term was originally used to describe the graphical representation of alternating-current voltage flow. Recognizing that the fluctuations of the alternative voltage flow between a positive maximum and negative minimum display an oscillatory pattern, it follows that the name oscillator is associated with oscillation or frequent fluctuation. (The term now more generally refers to an electronic device used for the purpose of generating a signal.) In technical analysis, the term *oscillator* refers to a wide range of techniques that can be based on substantively different calculations and motivations. The unifying notion connecting the techniques is that the chart pattern calculated from the original price chart oscillates or fluctuates within a defined range. The defined range for an oscillator permits the specification of *overbought* and *oversold* levels for the oscillator that can be used to identify trading signals. Interpretation of overbought and oversold signals is aided by the concept of *divergence*. Because the oscillator is often constructed by taking the difference of two series, most oscillators are designed to be ‘counter-trend’ systems. This leads to the following result (Schwager 1996, p. 556): “Oscillators perform well when a market is in a trading range — that is, a sideways trend. They work poorly, however, when a market is in a strong uptrend or downtrend”.

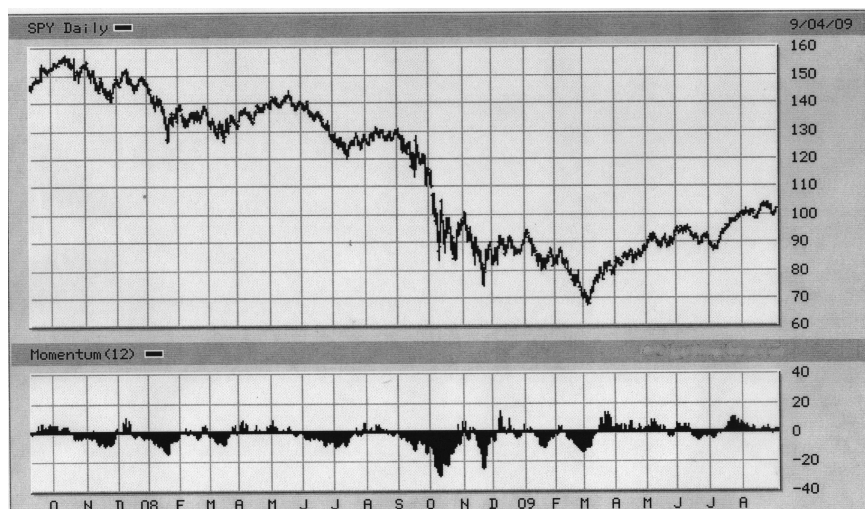


Fig. 6.13 Twelve-day momentum for SPY, 2008–2009.

The oscillator covers so many techniques that some technical analysis websites do not make any reference to the concept, e.g., [www.marketscreen.com](http://www.marketscreen.com), opting instead to list specific types of oscillators directly. Other sites use a narrow definition of oscillator that excludes many types of techniques that would be considered oscillators using a wider definition. An example of a narrow definition is found at [www.futuresource.com](http://www.futuresource.com) which defines an oscillator as “the simple difference between two moving averages”. Adopting the wider definition, momentum can be viewed as a type of oscillator. As illustrated in the bottom chart from Fig. 6.13, the momentum chart oscillates above and below the zero slope line.  $M(t, 1)$  is, arguably, the simplest form of oscillator. A number of more sophisticated oscillators, such as the Relative Strength Index and the Lane Stochastic, are developments on the momentum oscillator. Though some forms of oscillator, such as the Lane Stochastic, have been in use since the 1950s, the fascination with the oscillator is a relatively recent development in technical analysis, gaining popularity starting in the early 1970s. For example, the concept is given only passing recognition in Edwards and Magee (1966). Kaufman (1976, p. 91) restricts “the use of the term oscillator to a specific form of momentum, that which is normalized or expressed in terms of values ranging between +1 and -1 or +1 and 0”. This definition would include the Relative Strength Index and the A/D oscillator.



Fig. 6.14 MACD for SPY, 9/07-9/09.

In addition to oscillators based on momentum, a variety of alternative specifications are possible. In particular, another simple oscillator is the dual moving average (DMA) oscillator that is constructed by differencing two moving averages of different length:  $DMA(t, j, k) = \bar{P}(t, j) - \bar{P}(t, k)$  where  $j < k$  with the  $j$  period moving average being ‘fast’ and the  $k$  period moving average being ‘slow’. This oscillator is of interest because the moving average is a trend-following technique while an oscillator is a counter-trend technique. In effect, the **DMA oscillator** is designed to capture the momentum of the trend: “When the fast moving average is accelerating away from the slow one, prices are gaining momentum; when the fast moving average is decelerating toward the slow one, prices are losing momentum” (Schwager 1996, p. 524). The zero line is defined as the point where the two moving averages are equal. Unlike trend following systems that use the crossing of the zero line as a trade indicator, the DMA oscillator signals trades by specifying overbought and oversold regions on the DMA oscillator chart. It is also possible to examine divergence between the oscillator and the price chart. In the same fashion that using the zero line to signal trades will result in false signals and whipsaws in trading range markets, using the overbought and oversold regions will result in false signals in trending markets.

The DMA oscillator is a graphical representation of the dual moving average trading system that can be implemented directly on the price

chart. The analytical advantages that are gained by mapping particular price chart information into a different chart format are in this case, more-or-less, incidental. This suggests a natural extension of the DMA oscillator that does exploit the ability to map from the price chart to the oscillator chart: the Moving-Average Convergence-Divergence (*MACD*). Though in the form of an oscillator, the MACD is not usually referred to as an oscillator because the technique integrates both trend-following and counter-trend methods. Credited to Gerald Appel, the MACD constructs a **MACD line** by subtracting a 26-period EMA from a 12-period EMA (see Fig. 6.14).<sup>29</sup> This step is a special case of a DMA oscillator that uses specific sample periods for exponential moving averages. To generate trading signals the MACD technique proceeds to calculate the *signal line* which is a 9-period EMA of the MACD line. As illustrated in Fig. 6.14 it is conventional for MACD charts to also contain a histogram of the difference between the MACD line and the signal line (in black in Fig. 6.14). The histogram provides an oscillator-like chart that can be used to identify trades.

Because the signal line in the MACD involves taking a moving average of the price difference between two moving averages, the MACD can be classified as a ‘double-smoothed momentum indicator’ (Blau 1995). The process for determining trades using the MACD line and the signal line is described in Schwager (1996, p. 538):

The basic method for trading with MACD is to buy when the MACD line crosses above the signal line and to sell when the MACD line crosses below the signal line. However, entering and exiting trades based solely on MACD line-signal line crossovers results in frequent whipsaw losses. To make the best use of MACD, it is advisable to wait for crossovers that are preceded by divergence and confirmed by the subsequent price action of the market.

The MACD is the featured technical indicator at a number of high traffic websites dedicated to technical trading, including the e-trade site. Though usually classified as an oscillator, the MACD does differ from other oscillators in having better theoretical properties in trend following situations. For example, the website [www.trade10.com](http://www.trade10.com) provides the following observation about MACD: “the signals generated by the MACD are trend following, occurring after the market has made movement in a new direction. For this

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<sup>29</sup> Appel is a well-known technical analyst, publisher of the newsletter *Systems and Forecasts*, as well as a number of books on technical analysis, e.g., Appel and Zweig (1976) and Appel (1974).

reason the MACD is used more as a conformational tool of the trend and can be used in trading decisions when combined with other indicators and platforms for decision and strategies". As with the momentum oscillator, the MACD also requires interpretation of the scale. To partially adjust for this shortcoming, various technical analysis websites also report information on the stochastic.

A limitation of the momentum chart is difficulty in interpreting the scale. In other words, when is the value of the oscillator 'high enough' to be overbought and 'low enough' to be oversold? A number of popular oscillators, such as the *Relative Strength Index* (RSI) and the Lane Stochastic are designed to produce a momentum indicator that has a scale varying between 0% and 100%. This scaling permits the overbought and oversold regions to be specified in a transparent fashion. Conventionally, overbought is >80% and oversold <20%, though >70% and <30% are also popular boundaries. The methods required to produce such scaling are not obvious. For example, at time  $t$  the RSI developed by Wilder (1978), is calculated as

$$RSI(t, k) = 100 \left( \frac{RS(t, k)}{1 + RS(t, k)} \right)$$

where  $RS$  is the weighted average of daily price increases over the past  $k$  days divided by the weighted average of daily price decreases over the previous  $k$  days. Wilder used  $k = 14$  days but this is not essential. Though the method of calculating the weighted averages requires detailed explanation, the intuition is clear: if there are a long string of up moves then  $RS$  gets large and  $RSI$  goes to 100; if there are a long string of down moves then  $RS$  goes to zero and  $RSI$  goes to zero.

As noted previously, it is not possible in a single chapter to examine in any detail the wide array of possible methods that could be used in technical analysis. Even if the subject is narrowed to just include oscillators, the topic is still unmanageable. Despite having examined momentum oscillators, DMA oscillators, the MACD and the RSI, the number of undiscussed oscillators still includes: Williams %R, similar to the stochastic oscillators; volume oscillators; the Ultimate oscillator, that uses the weighted sum of three oscillators; detrended price oscillators; Lane's fast and slow stochastics, based on the location of closing and opening prices within the high-low range; the mass index, based on the high-low range; the McClellan oscillator, based on the number of advancing and declining issues; the True Strength Index (Blau 1995, p. 5); candlestick momentum; and the

stochastic momentum index. Beyond the basic description of these oscillators, there is also a need to describe practical issues about the implementation. All this would take more space and time than is practical here. Those wanting more information are recommended to visit a number of the excellent technical analysis websites such as [www.futuresource.com](http://www.futuresource.com) and [www.marketscreen.com](http://www.marketscreen.com).

## Appendix: The Story of Richard Hanks

I only met Richard ‘Dick’ Hanks once that I can recall — my mother, Dick and I played nine holes of golf together sometime around 1970. What I know about Dick comes from my mother. Dick was a close friend of my mother and her second husband, Ted. In the decade or more following Ted’s death, my mother took care with Dick — bringing him over to the house each week for dinners and the like — until he also passed away a couple of years ago after a long battle with COPD. Dick’s story is relevant here because of the tragic role that the arcane theories of technical analysis played in his life. The securities markets are impersonal battlegrounds and *caveat emptor* applies to those seeking to profit from any of the sophisticated and not so sophisticated speculative trading strategies associated with valuations determined using technical analysis. Numbers, charts and mathematics can give naive investors the impression that the valuations are backed by scientific analysis. Unfortunately, the feedback effect prevents such a scientific foundation from being legitimately established.

Dick was a well educated, upper middle class American living in the Burien suburb of Seattle. He was a successful electrical engineer with Boeing and was able to retire at a relatively young age. His family was well off and he inherited a genteel fortune when his father passed away. When I met him, Dick was retired. He owned a 38-foot sailboat, a home on the first hole Glen Acres golf club and had ample funds for regular vacations to California, Mexico, and Hawaii. It is likely that, at some point, this retirement lifestyle became inconsistent with the cash flow from the underlying portfolio of retirement assets and Dick had to find additional sources of funds to avoid depletion of capital. Like so many before him, he decided that the stock market was the appropriate El Dorado. Being trained as an engineer, Dick understood the importance of researching a subject in depth. His engineering training likely also led him to believe in closed loop systems which are controllable and predictable. The jump to a belief in the tools of technical analysis was understandable. Dick was smart enough to interpret the charts but not cynical enough to question the associated valuations.

Dick's had some initial success with his stock investments and, like my mother, benefitted during the mid-1980s from the advice of a particular stock broker who recommended a number of local NW stocks, including Microsoft. At some point, Dick abandoned the advice of this stock broker and had taken over effective control of stock selection. It was not until the market downturn in the early 1990s that Dick was hit with severe enough losses that he was left penniless. The ideas that guided his selection strategy became apparent as I helped my mother and his nephew clean out his small apartment. The apartment itself was a dreary unit, funded through the federal Section 8 program for those unable to pay rent. Amongst the items in his book collection were various tomes by stock market soothsayers. Most prominent was a well worn copy of the sixth edition of the classic text on technical analysis by Edwards and Magee (1992; first ed. 1948). Various chapters, including those on gaps, trendlines and channels, were heavily marked with high-lighter and accompanied by detailed margin notes. Dick would surely have been impressed that the New York Institute of Finance was responsible for publishing this edition of the 'universally acclaimed investor's classic'.

Having my interest piqued by the discovery of Edwards and Magee, as we sorted through the stuff in Dick's apartment I had my mother relate a number of vague anecdotes about Dick's trading strategies. Dick was exclusively a 'long only' investor. Though he did not begin with the practice of buying stocks with borrowed money, by the end he was doing so in the hope of recouping previous losses. Initially, only a portion of his retirement portfolio was dedicated to technical trading though the percentage increased over time to the point where losses on technical trading exhausted the capital in the portfolio. As well as I can determine, Dick was initially successful in using technical analysis to select stocks. At some point, he was convinced that the charts for a number of stocks had achieved a particular formation. When this proved to be wrong, the losses only strengthened his resolve and he added to his positions. The tragic consequences of his particular conclusion to the gambler's ruin problem was all too apparent in the dilapidated furniture I loaded onto my truck for removal to the dump.

The lessons from the story of Richard 'Dick' Hanks are relevant for users of technical analysis because these were the tools guiding the equity security trading that, ultimately, led to Dick's financial ruin. Whether it was technical analysis that was to blame or whether it was failings in his trading methods is not clear, but the warning signs are clearly there. The analytical basis for such tools is opaque, at best, and users need to exercise



appropriate caution. Given this caveat, there were also general failings in trading practices that would have impacted Dick's results whatever equity security valuation techniques he used. Included in these failings was over confidence. Initially, Dick met with some success using technical analysis to select stocks. The confidence this created strengthened his resolve to hold or add to a position when facing substantial losses. Variations on the 'double up' strategy to recoup losses can produce disastrous consequences. 'Cut losses and let profits run' is an old adage of seasoned speculators in the futures pits. Another key failing was speculating in equities with borrowed money.

The 'get rich quick' allure of the equity market is reinforced by the anecdotal success stories that appear on a daily basis in the financial press. Such stories date back to the beginnings of trading in equity securities. This 'get rich quick' theme pervades much of the lore of the stock market and includes some fascinating stories: the bear speculator Claviere enlisting Mirabeau in his schemes to manipulate stock prices prior to the French revolution; the U.S. stock operators and the option pools of the 1920s; and, the global hedge fund managers on the eve of the millennium. The connection with pictures of 'Powerball' lottery winners and World series of poker features on cable TV is apparent. However, Dick Hanks would almost certainly not have borrowed money to gamble on lottery tickets or thought he could make a living playing cards in Las Vegas. Gambling in the stock market is, somehow, different than other forms of gambling. The often untold story is about the 'fleecing of the lambs', those who were induced into gambling in equities and lost, with tragic consequences.

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