

Chapter Summary

Chapter 9 *Technical Analysis Demystified*

- 9.1 What is Technical Analysis?
 - A. Different Forms of Technical Analysis
 - B. Conceptual Foundations of Technical Analysis
 - C. Modern Finance and Technical Analysis
- 9.2 The Technician's Toolkit
 - A. The Dow Theory
 - B. Charting and Moving Average Systems
 - C. Contrarian and Contrary Opinion Strategies
- 9.3 Behavioral Foundations?
 - A. Heuristic-Driven Bias
 - B. Frame Dependence
 - C. Inefficient Markets
- 9.4 Relative Strength, Momentum and the Oscillator
 - A. Relative Strength
 - B. Momentum and the 'Price Rate of Change'
 - C. Oscillators

End of Chapter Questions

Notes

Chapter 9 *Technical Analysis Demystified*

9.1 What is Technical Analysis?¹

A. Different Forms of Technical Analysis

Much like ‘fundamental analysis’ (see sec. 7.2), ‘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). 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), Ready (2002).²

What can be concluded from the apparently conflicting empirical evidence that is now found in the body of academic studies on technical analysis? Does technical analysis provide effective methods for enhancing investment portfolio profitability through, say, improvements in market timing ability? This chapter does not attempt to answer these questions. Rather, this chapter seeks only to provide an overview of the subject, describing various methods of technical analysis and identifying relevant studies that may give insights into the validity of specific techniques.. Those seeking information about, say, the “statistically significant evidence ... from momentum profits” in Chan (2002) are encouraged to examine the relevant sources directly. While there are many methods of technical analysis that fail to produce substantive improvements, it is difficult to deny that virtually all purchases of common stock and other securities involve at least a rudimentary form of technical analysis, i.e., an inspection of the historical price chart. Beyond this basic starting point, the application and extension of technical analysis tends to be a relatively subjective decision.

Much like fundamental analysis, technical analysis is an important, diverse and sometimes complicated approach to the evaluation of securities that has been overly simplified in tests of the ‘weak form’ efficient markets hypothesis (see sec. 1.2). The methods and procedures involved in taking a body of ‘technical information’ and translating that information into an evaluation of whether a stock is correctly valued does not 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 speculative trading***, not with investment. 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. 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 may be 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 weekly 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 1970's 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 commodity trading. 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 has created a resurgence of contributions concerned with stocks, e.g., Elder (1993), 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, www.futuresource.com or clearstation.etrade.com.

B. Conceptual Foundations of Technical Analysis

The current debate over the merits of technical analysis can be traced back to the beginnings of modern Finance in the late 1950's and early 1960's. 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” (see sec. 2.4), if only because of the emphasis on speculative trading strategies.³ Technical analysis, in some form or other, has been practiced in securities market at least since the 16th century (Poitras 2000). Nison (1996) finds evidence for the use of technical analysis in 18th century Japan. 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.

Though a definitive intellectual history of technical analysis is yet to be written, the origin of modern technical analysis is usually traced to the late nineteenth century when Charles Dow originated the Dow-Jones Industrial Index.⁴ Together with his successor at the *Wall Street Journal*, William Peter Hamilton, Dow was an active promoter of technical analysis 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, Dodd and Cottle (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 that security price changes were serially uncorrelated which started to accumulate during

the 1950's (see sec. 1.2).⁵ 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?⁶ In the process of making a headlong rush to judgment, modern Finance was quick to dismiss conceptual arguments supporting the foundations of technical analysis.

While specific rationales for technical analysis have appeared more recently – such as behavioral finance motivations (Shefrin 2000) – Levy (1966) provided an assessment of the conceptual foundation for technical analysis prevailing at the time the efficient markets hypothesis was being formulated. A summary of this assessment can be stated as:

1. Market value is determined 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.

The connection with behavioral finance appears in point 2. The connection with chartism is associated with point 4 where the detection of market action is achieved through the use of charts. The notion is that certain chart patterns will tend to recur and these patterns can be used to make forecasts of prices.⁷

Levy (1966) is not the only statement of the conceptual framework for 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.*** Though reference is made to ‘all relevant information’ being incorporated into prices, hiding in the background is a view of security pricing that is decidedly contrary to the view of security pricing contained in the Graham and Dodd approach (see sec. 7.4). 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 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 (see sec. 7.3).

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 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 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 (see sec. 1.3). 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.⁸ 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.

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, p.714-5):

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?

Referring to the Levy (1966) four point conceptual foundation for technical analysis given above, all four points 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 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.

C. Modern Finance and 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 positivist philosophy that drives the subject, the process of ‘empirical verification’ has guided this change of course. 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 1990's, 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 to 1929 ... Neural net modeling to replicate Hamilton’s calls provides interesting insight into the Dow Theory” (Brown et al. 1998).

The evidence in favor of various 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 (see sec. 1.2). The scope of these studies includes evidence for: pricing anomalies, such as the January effect and the small firm effect (see sec. 1.2), e.g., Dimson (2002); serial correlation in returns, e.g., Campbell et al. (1997), 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 (2000).⁹ 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 that seeks to explain deviations from market efficiency in terms of investor psychology. Strong prior beliefs will encourage those with attachments to the prevailing theory to question the statistical results in favor of the new theories, presenting claims such ‘data-snooping’ or ‘data-mining’. Others proceed 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 (see sections 3.2 and 3.3), 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 riskfree interest rate, 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 security investment opportunities. However, the CAPM is decidedly unlike technical analysis in being derived from a coherent theory of equilibrium pricing.

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 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, in the absence of a well-developed theoretical foundation for, say, the inclusion of ‘value factors’ in asset pricing models, it is difficult to determine why this approach is immune from the criticisms that Graham and Dodd aimed at technical analysis. To see this, consider the following tongue-in-cheek adaptation of the four points raised against technical analysis:

1. Asset price modeling cannot possibly be a natural 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 asset pricing students increases.

Despite being tongue-in-cheek, there is a ring of truth in this version of the four points raised by Graham and Dodd against technical analysis.

In particular, consider the question: Why cannot asset price modeling be considered a natural science? The answer to this question was discussed in detail in sec. 1.3 – the human sciences cannot operate under the same ground rules as the natural sciences. Just as with technical analysis, using asset price modeling to identify securities that will generate abnormal returns is also subject to the ‘feedback problem’. Other aspects of the four points follow appropriately. By abandoning the 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. Even the third point can be rationalized by referring to the severe limitations (faulty logic) that apply to the perfect capital market assumptions that are used to derive the asset pricing models of modern Finance.

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 modern Finance is constructed. It is the ‘Keynesian convention’ (see sec. 9.3) that is used to deal with the uncertainty arising in security analysis and investment strategy, 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 and refusing to reveal the forecasting system that is being used to identify the trend. Academic researchers cannot take refuge in this approach.

9.2 The Technician’s Toolkit

A. *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 (see sec. 2.3).¹⁰ 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 theory’.) Reference to the “**Dow’s theory**” can be traced to a collection of these editorials that was published by S. Nelson, 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 1903 and 1929.¹¹ 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 US 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 died shortly after bringing the theory on line, Hamilton died in 1930 shortly after writing his last editorial on Oct. 25, 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 July 8, 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 1930’s, 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.¹²

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): “[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 to 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): “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.

INSERT Table 9-a DJTA (see tab_10-a.xls)

INSERT Figure 9-1 Example of a Dow Theory Confirmation Signal

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 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) having to be considered in conjunction with an analysis of changes in the Dow-Jones Transportation Average (DJTA) (see Table 9-a). The confirmation of these two signals is usually expected to be accompanied by a high level of trading volume on the confirmation date (see Figure 9-1 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.

INSERT Figure 9-a, 5 year DJTA chart

INSERT Figure 9-b, 5 year DJIA chart

As is evident from an inspection of Figures 9-aa and 9-bb, *identification of confirming signals* in the DJIA and DJTA is not an obvious exercise. For example, has a confirmation signal been achieved on March 11, 2003? Though it came close, the low in the DJTA that occurred in March 2003 was not quite confirmed by the DJIA which 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. Comparing Figures 9-aa and 9-bb with the stylized example in Figure 9-1, it appears that the Dow theory has not produced a strong signal for the end of the primary bear market

trend that began in May 1999. However, the market trading environment has changed significantly since Dow, Hamilton and Rhea developed the corpus of the theory.¹³ For example, as illustrated in Table 9-a, 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 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 that the events of 9/11 had on the airline industry – if only because the impact on airline valuations has reduced the share of this component in the DJTA. Perhaps this is an instance where the theory will fail to give a clear signal. Or, perhaps the structural changes in the securities markets and the economy have rendered theory ineffective for the foreseeable future. It is difficult to tell.

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; 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 pullbacks 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 recognizes the possibility that the global low point for the DJIA in the current primary bear market trend will not be confirmed by the DJTA. Rather the bottom will come when the DJTA hits a global low and the DJIA hits a (local) low that is followed by an, unconfirmed, global low (or vice versa). This is something of a disconnect from the old-style Dow theory that, implicitly, assumed that the DJTA and DJIA confirmation would be associated with global values.

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 US 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. 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. beg 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 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 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.

B. Charting and Moving Average Systems

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 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 security analysis or investment strategy 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. Similarly, the valuation process for, say, a corporate bond will examine the time series for credit spreads, yield curve shape and yield levels. Technical analysis attempts to bring more structure to this process. In the absence of a unified theoretical foundation, the resulting 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.¹⁴ 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 or index values

plotted using an arithmetic scale (see Figures 9-a and 9-b). 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”.

INSERT Figure 9-c Bar Chart S&P 500 futures
 INSERT Figure 9-e Candlestick Chart S&P 500 futures

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 Figure 9-c); point-and-figure charts; and Japanese candlestick charts (see Figure 9-e). **Point-and-figure charts** (not discussed here) are specialized charts more commonly used in futures markets, particularly by floor traders and day traders, than in stock markets.¹⁵ These charts do not take account of time but, rather, view trading as a continuous process. For technical analysis of security prices, **the bar chart** is the most common type of chart. As indicated in Figure 9-c, for a daily bar chart each day is represented by a vertical line defined by the high and low prices for the day with a small horizontal line indicating the close. 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 can generate more signals than bar charts. In effect, a candlestick chart contains all the information available in a bar chart and more. Because a candlestick chart has more information it is also somewhat more complicated and requires more preparation effort. While such charts are available at publicly accessible internet futures charting services such as www.futuresource.com (see Figure 9-e), the format is currently only available at pay-for-service stock charting services, e.g., www.stockchart.com. The bar chart is still the standard format for stock charts. Casual inspection of a bar chart reveals that while the high, low and close are indicated, there is no information about the open and the relationship between open and close. This information is included in the candlestick chart. The thin line on a given day gives the high and low while the white and black boxes – called “real bodies” – reflect the open and close. A black (white) 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).

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. The one hammer in Figure 9-e was followed by a strong up move the next two trading sessions. 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.¹⁶ More detail on these issues can be found in Nison (1991, 1996) and at websites dedicated to technical analysis such as www.marketsource.com.

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 other are amazingly regular or “normal”, produced in a series of action and reaction waves of great uniformity. Sooner 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.

INSERT Figures 9-f and 9-ff S&P 500 (SPY) 1 and 3 year

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 Figure 9-f that provides a 1 year and 3 year bar chart for the S&P 500 (SPY). The trend line for the 1 year chart indicates that the downtrend has been broken in March 2003 while for the 3 year chart the relative high would have to be close to 100 for SPY (1000 on the S&P 500) before the trend line is broken (see end of chapter questions). Schwager (1996, p.25) captures the type of conclusion that can 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.”¹⁷

INSERT Figure 9-g Trading Range for PG

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).¹⁸ An example of a trading range is provided in Figure 9-g, where the 1 year price movement of Procter and Gamble is bounded above by \$95 and below by about \$75. 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. 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 (see sec. 9.4) 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 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” (see Figure. 9-g).

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, p.67-9) 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 Figure 9-f 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.”

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 (see sec. 9.4). 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 averages at time t are calculated as:

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

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 (≥ 0) weights is required to be equal to one. The simple moving average weights each of the observations equally ($1/T$). Variations of the weighted moving average approach, such as the exponential moving average (see end of chapter questions), 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 $w_i = 1/T$.

Insert Figures 9-h1 200 day vs. 10 day MA chart for SPY, 7/98 to 7/03

Insert Figures 9-h4 50 day vs. 10 day MA chart for SPY, 11/02 to 7/03

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 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 moving average can be used to identify the trend. Due to the lagging nature of a moving average, in a rising market the moving average value for a given date will lie below the price for that date. Conversely, in a declining market the moving average will lie above the current price (see Figures 9-h1 and h4). Trend reversals, **crossovers**, occur when the sequence of current prices crosses the moving average. 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, e.g., a 200 day moving average is compared with 10 day moving average as in Figure 9-h1.¹⁹

Insert Figures 9-j.pg1 and 9-j.pg5 PG 50 vs 10 day MA, 1 and 5 year samples

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 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 Figure 9-h1, it is apparent that the S&P peaked in mid-2000, the price series did not provide a confirmed crossover until almost a year later. The 50

day moving average gives much better results, though there is a hint 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. The 10 day moving average is replete with whipsaws and would only generate useful trend signals when the trading interval is short, e.g., day-to-day trading. While the 50 day moving average appears to work well for the S&P 500 the failings of the moving average in a trading range market are apparent in Figures 9-j.pg1 and 9.j.pg5 which provides results for 10 and 50 day moving averages for Procter and Gamble over a one year and 5 year sample period. Selecting the appropriate length for a moving average is a subject of considerable debate and study by technical analysts, e.g., Kaufman (1978, p.83-5). Further developments of moving average systems are discussed in sec. 9.4.

INSERT Figure 9-xx 1 year Advance-Dcline Line for the DJIA

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 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). 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 (see Figure 9-xx). The weekly advance-decline line total is then plotted as in Figure 9-xx. An alternative method of calculation is to sum the advance decline ratio – the ratio of advancing issues to declining issues.²⁰ 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 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.

C. Contrarian and Contrary Opinion Strategies

Like ‘value’ and ‘growth’ stocks, the ‘contrarian approach’ to security analysis and investment

strategy is another 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). Levis and Liodakis 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 old Finance or in practitioner 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 a seemingly chauvinistic attitude regarding previous approaches to the subject. Redefining words that already have established alternative meanings – such as ‘contrarian’ investment strategy – shows either ignorance of other approaches to Finance or a disappointing lack of respect for these approaches.²¹ 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 attempt by adherents of modern Finance to redefine the contrarian approach is unfortunate because the long history of the contrarian approach contains many insights. The basis of this approach to security analysis and investment strategy 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 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 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 1950's. 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-1950's:

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 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, p.44-6), 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 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) 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 Figure 9-m2).

Insert Figures 9-m.2 Investor’s Intelligence NYSE Bullish

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.

9.3 Behavioral Foundations?

A. Heuristic-Driven Bias

The 'discovery' in modern Finance that technical analysis may provide a source of profitable trading rules has resulted in a rejuvenation of psychological explanations of market behavior, albeit with a modern twist. This empirically driven rejuvenation has been greatly aided by the experimentally based "*prospect theory*" of Kahneman and Tversky (1979) (see sec. 10.4). The view that psychological factors play an important and, at times, an overriding role in securities markets has been around for centuries. From de la Vega in the 17th century to Keynes in the 20th century, the tension between bulls and bears has fascinated market observers. The importance of psychological factors to professional security analysts was recognized in GDC (p.712):

In recent years the psychosomatic element in illness has been emphasized to such an extent that most doctors apparently have to be psychologists. In the security field a like situation has obtained almost from the beginning. Security analysts have felt the need to gauge the psychology or "technical position" of the stock market and to base their buying and selling recommendations on a combined consideration of underlying value *and* prospective market movement.

This suggested combination of technical analysis with "value" considerations has attracted considerable recent attention in modern Finance, e.g., Chan et al. (1998), Macedo (1995).

While the impact of psychological factors on stock markets and prices has a long history, the most recent developments have been gathered under the heading of "behavioral finance". Characterized as the "New Finance" by Haugen (see sec. 2.4), this 'new subject' has been propelled by a desire to provide explanations for the empirical failings of modern Finance that have emerged in the form of 'anomalies' (see sec. 1.2). Though decidedly more inductive, the philosophical and rhetorical approach of behavioral finance is consistent with the positivism of modern Finance.²² As such, intellectual roots and historical progression of behavioral finance have been clouded by the perception that, somehow, the subject is a new evolution of the positivist approach. For example, Shefrin (2000, p.ix) claims: "Phil Cooley was among the first to apply the findings of psychologists and study the risk attitudes of portfolio managers, he published his work in the 1977 *Journal of Finance*. In fact, most of the major contributions to behavioral finance have appeared in academic journals." The connection between this statement and McCloskey's observation about the rhetorical aspects of 'conversations between academics' (see sec. 1.3) is difficult to avoid.

The claims of behavioral finance academics for being "first to apply" this or that notion to practical financial applications is, at best, overstated. Consider the '*heuristic-driven bias*' that Shefrin (2000, p.4) identifies as one of three central themes in behavioral finance:²³

Do financial practitioners commit errors because they rely on rules of thumb? Behavioral finance answers yes, and traditional finance answers no. Behavioral finance recognizes that practitioners use rules of thumb called heuristics to process data. One example of a rule of thumb is: "Past performance is the best predictor of future performance, so invest in a mutual fund having the best five-year record." Now, rules-of-thumb are like back-of-the-envelope

calculations – they are generally imperfect. Therefore, practitioners hold biased beliefs that predispose them to commit errors. For this reason, I assign the label heuristic-driven bias to the first behavioral theme. In contrast, traditional finance assumes that when processing data, practitioners use statistical tools appropriately and correctly.

There are a number of oddities about the claims made in this statement. One oddity is that modern Finance is referred to as “traditional finance”, as though Graham and Dodd and other contributors to Haugen’s “Old Finance” (see sec. 2.4) were non-events. Intellectual progress is being measured relative to the inadequacies of modern Finance, as though Philip Fisher, J.M. Keynes, Ben Graham and a range of others that made essential insights into securities markets had never contributed anything of substance. Conversations that took place outside the narrow confines of the academic circle of modern Finance are irrelevant, even though these conversations still have considerable relevance to behavioral finance.

To see the basis of this point, consider the following from J.M. Keynes (1936, ch.12, p.149-50):

The outstanding fact is the extreme precariousness of the basis of knowledge on which our estimates of prospective yield have to be made. Our knowledge of factors which will govern the yield of an investment some years hence is usually very slight and often negligible. If we speak frankly, we have to admit that our basis of knowledge for estimating the yield ten years hence of a railway, a copper mine, a textile factory, the goodwill of a patent medicine, an Atlantic liner, a building in the City of London amounts to little and sometimes to nothing; or even five years hence. In fact, those who seriously attempt to make any such estimate are often so much in the minority that their behavior does not govern the market.

For Keynes, the “uncertainty” that impacts financial decisions requires practitioners to employ “*convention*”. In the words of Keynes (1936, p.152): “In practice, we have tacitly agreed, as a rule, to fall back on what is, in truth, a *convention*. The essence of this convention, though it does not, of course, work out quite so simply – lies in assuming that the existing state of affairs will continue indefinitely, except insofar as we have specific reasons to expect a change.” Compare this with the heuristic given by Shefrin: “Past performance is the best predictor of future performance, so invest in a mutual fund having the best five-year record.” Yet, Keynes goes well beyond the notion of heuristics to develop an insightful theory on the working of financial markets. This is not to say that the theories proposed by Keynes were correct. Rather, the pre-modern Finance contributions made by Keynes and others are not even acknowledged.

Keynes was far from being the only precursor of the ideas that behavioral finance is claiming to be the ‘first’ to apply. Consider Neill (1954, p.55-7):

Habit, of course, is one of the chief studies of psychology. Habits are of various types: fixed and changeable; likewise, physical, mental, and emotional. William Henry Mitchell tells us that “every division of the mind is habitualized ... Through habits we develop routines of action and thinking. This applies to business and financial thinking just as it does to the daily routine of eating and dressing ... Habits push our minds into ruts – and it takes a considerable amount of force and time to get out of the ruts. So, in contemplating crowd action (to which we may wish to be contrary) we have to consider not only the thought-habits of the crowd but our own thought-habits! This “rut-thinking” is regularly reflected in economics, politics, and in the stock market.

This connection between ‘habits’ and financial decisions is not substantively different than the ‘heuristics’ proposed by behavioral finance. Yet, Neill proposes a way of thinking that will permit the individual to avoid the “biased beliefs that predispose them to commit errors”, as Shefrin describes the implications of decision-making using heuristics. In contrast, behavioral finance seeks

to use heuristics to explain empirical observations that run contrary to received opinion in modern Finance. Neill provides sufficient references to indicate that these ideas about the implications of ‘habits’ were relatively well developed by the 1950’s. Because behavioral Finance shares the same positivist roots as modern Finance, there is a shared belief that ‘science’ progresses linearly and ideas and insights from the past have been superseded by the progress of knowledge. As discussed in sec. 1.3, this incorrectly assumes that Finance is a natural science and not a human science.

All this is not meant to imply that behavioral finance is a watered down rehashing of unacknowledged ideas that were developed much earlier and in more insightful fashion – quite the contrary. Behavioral finance has extended and clarified notions that were, in some respects, relatively disorganized and underdeveloped. In particular, even though the implications and use of heuristics in financial decision making has long been recognized, behavioral finance provides a fresh and typically more developed perspective. Consider the evidence that buying losers and selling winners is profitable, e.g., De Bondt and Thaler (1985, 1987). Behavioral finance explains this outcome as a consequence of using stereotypes as a heuristic to make judgments, a practice that Kahneman and Tversky (1979) refer to as “*representativeness*” (Shefrin 2000, p.14). The stereotyping of past winners and losers causes ‘overreaction’ by analysts and stock traders. Shefrin identifies a range of other manifestations of heuristics such as availability bias, aversion to ambiguity, hindsight bias and overconfidence. “Because of their reliance on heuristics, practitioners hold biased beliefs that render them vulnerable to committing errors” (Shefrin 2000, p.22). These errors can lead to the anomalies observed in a range of empirical studies that challenge the efficient markets hypothesis.

B. Frame Dependence

Frame dependence is an obscure terminology that describes a range of interesting psychological responses to investment situations. Following Shefrin (2000, p.4): “Behavioral finance postulates that in addition to objective considerations, practitioners perceptions of risk and return are highly influenced by how decision problems are framed.” ***Loss aversion***, also known as the “disposition effect”, is a useful example of frame dependence. Nofsinger (2002, p.22) illustrates loss aversion with an investment situation where an individual wants to purchase a stock but has no cash and has to sell one of two stocks to raise the required capital:

Stock A has earned a 20% return since you purchased it, whereas stock B has lost 20%. Which stock do you sell? Selling stock A validates your good decision to purchase it in the first place. You enjoy pride at locking in your profit. Selling stock B at a loss means realizing that your decision to purchase it was bad. You would feel the pain of regret. The disposition effect predicts that you will sell the winner, stock A. Selling stock A triggers a feeling of pride and avoids regret.

Loss aversion also leads to the “get-evenitis” disease, i.e., the extreme reluctance of individual investors to sell at a loss, which “has probably wrought more destruction on investment portfolios than anything else” (Gross 1982). The upshot of loss aversion is a tendency to sell winners too early and hold losers too long, e.g., Shefrin and Statman (1984). If present, the reduced returns associated with this tendency would be compounded by the adverse tax consequences; selling winners generates a taxable capital gain while selling a loser generates a capital loss that can be used to offset capital gains.

Behavioral finance aims to provide theoretical explanations to support empirical results contrary to the prescriptions of modern Finance. As such, frame dependence is a key theme in behavioral Finance because modern Finance assumes that individuals are frame independent. In addition to empirical anomalies such as the January effect and the small firm effect that appear to contradict the efficient markets hypothesis, there are a number of other empirical phenomena that provide puzzling examples of possibly irrational behavior. Perhaps the most significant example of such irrational behavior is the “*dividend puzzle*”, e.g., Frankfurter (1999). This puzzle arises because investors consistently express a preference for dividends over capital gains, despite the unfavorable tax treatment of dividends. This preference is reflected empirically in the prices of stocks, as well as in investor surveys. The theoretical prescription that modern Finance advances to explain rational behavior toward dividends, the dividend irrelevance hypothesis of Modigliani and Miller (M and M), provides a popular illustration of frame independence. Underlying this hypothesis is the assumption that individuals will be guided by the desire to achieve the most favorable cash flow and will be indifferent between capital gains or dividends if the cash flows (end of period wealth) are not affected.

To derive the *dividend irrelevance hypothesis*, M and M proceed by assuming perfect markets. In the case of dividend payout, perfect markets is a conservative assumption because it ignores the negative tax implications of dividend payments. An all-equity financed firm is faced with two choices: paying dividends and financing further expansion by issuing additional stock; or foregoing dividend payments and using retained earnings to finance expansion. Using an arbitrage argument, M and M demonstrate that the dividend policy of the firm is irrelevant because, in the event the firm decides to forego paying dividends, investors can create synthetic or “homemade” dividends by selling stock. The increase in the stock price in the no-dividends case will be just sufficient to compensate for the value of dividends that would have been paid in the dividend-payout case. The equity claim against assets is the same in both cases, though the number and price of shares will differ over time to reflect the new issue of shares in the dividend payout case and the increase in stock price for the retained earnings case due to the enhanced claim against assets. In the dividend payout case, the investor has cash in hand from dividends that is just equal to the cash in hand received from the sale of stock in the retained earnings case.

There are a range of effects that fall within the scope of frame dependence including: hedonic editing; self-control; cognitive dissonance; the snake bite; and money illusion. Both hedonic editing and the desire to achieve self-control can be used to motivate a psychological explanation for the dividend puzzle. *Hedonic editing* applies to the M and M dividend irrelevance case because (Shefrin 2000, p.29): “hedonic editing offers some insight into investors’ preferences for cash dividends. When stock prices go up, dividends can be savored separately from capital gains. When stock prices go down, dividends serve as a ‘silver lining’ to buffer a capital loss”. Another reason given for the preference of dividends over capital gains is self-control (Shefrin 2000, p.30):

Older investors, especially retirees who finance their living expenditures from their portfolios, worry about spending their wealth too quickly, thereby outliving their assets. They fear a loss of self-control, where the urge for immediate gratification leads them to go on a spending binge. Therefore, they put rules into place to guard against the temptation to overspend. “Don’t dip into capital” is akin to “don’t kill the goose that lays the golden eggs.” But if you don’t dip into capital, how do you finance consumer expenditures – Social Security and pension checks alone? Not necessarily – this is where dividends come in. Dividends are labeled as income, not capital. And investors tend to frame dividends as income, not capital. Again, this is frame dependence.

Being a relatively new subject, the terminology for the various effects does differ. For example, Nofsinger (2002, p.87) classifies this process of not dipping into capital under the general category of “mental accounting”.

Following the approach used by Kahneman and Tversky (1979), behavioral finance typically proceeds by the use of stories, experiments and exercises. Though there are empirical studies that tend to support certain behavioral explanations, there are others that suggest the opposite. For example, Fama (1998) observes: “apparent overreaction to information is about as common as underreaction, and post-event continuation of pre-event abnormal returns is about as frequent as post-event reversal. Most important, consistent with the market efficiency prediction that apparent anomalies can be due to methodology, most long-term return anomalies tend to disappear with reasonable changes in technique.” To be sure, there are numerous empirical studies that are supportive of specific theoretical propositions advanced by behavioral finance. However, by proceeding along a positivist line, it is necessary for the results to be unambiguous and capable of rejecting appropriate alternative hypotheses. This goal has, to date, not been achieved. In the absence of convincing empirical evidence, the strength of the behavioral finance case relies heavily on stories and experiments – these are slender reeds to support the intellectually ambitious agenda of behavioral finance.

C. Inefficient Markets

The last of the three central themes of behavioral finance identified by Shefrin (2000, p.5) is market inefficiency: “heuristic-driven bias and framing effects cause market prices to deviate from fundamental values.” The implication is that due to the pervasiveness of psychologically driven trading behavior, security markets will be inefficient. Behavioral finance seeks to provide explanations for why security markets can be inefficient. Yet, considerable confusion is created by the inductive character of this process. An empirical result is presented, such as a return anomaly, that is claimed to represent a market inefficiency, somehow defined. A behavioral explanation is then developed to account for the empirical result. Presumably, if the market is inefficient, the behavioral explanation would provide a method for identifying and understanding situations where abnormal returns can be obtained. Yet, beyond the original empirical result that identifies the anomaly, behavioral finance provides little guidance for “picking stocks to beat the market”. It is difficult to shake the notion that behavioral finance does not proceed much beyond providing explanations for pricing inaccuracy, as opposed to pricing inefficiency.

The basic definition of market efficiency relates to security prices fully and rapidly reflecting the information contained in technical or fundamental or insider information sets (see sec. 1.2). If a market is inefficient with respect to a given information set then it is possible to use that information to generate an abnormal return. Yet, Shefrin (2000, p.89) makes the following statement:

... it is harder to beat the market than most people think. That is an important reason why the moral ... is *not* that investors can use behavioral finance to make a killing. I think most investors would be better off holding a well-diversified set of securities, mainly in index funds, than they would be trying to beat the market [using behavioral finance]. In other words, they would be better off acting as if Fama were right, that markets are efficient.

Hence, while behavioral finance can provide explanations for empirical ‘return anomalies’ that

indicate market inefficiencies, Shefrin does not put much credence in the potential for using such anomalies to actually generate an abnormal return. This view is not unique to Shefrin. For example, after detailing the contributions of behavioral finance, Nofsinger (2002, p.87-9) proposes the following guide to “beating the biases”: understand the biases; know why you are investing; have quantitative investment criteria; diversify; and, control your investing environment. This guide does not suggest any potential for generating abnormal returns. Rather, the advice mostly concentrates on avoiding abnormal losses that can beset the novice investor.

Based on Shefrin (2000, p.89), the absence of a connection between behavioral finance and market inefficiency is difficult to deny: “What about investing based on learning some behavioral finance? Well, understanding the relevance of representativeness means having a little knowledge, and you know what they say about a little knowledge. It is a dangerous thing.” Is there any usable advice that security analysts or individual investors can find in behavioral finance to generate abnormal returns? Much like Nofsinger, Shefrin provides advice that is largely useful for novice investors:

The moral of the [behavioral finance] story, for most investors, is not to be overconfident. Markets may fail to be efficient, but that doesn't mean it's easy to beat the market – either by oneself or by relying on the advice of some guru ... If an investor picked just one brokerage firm in 1986 and stayed with it for the duration, the odds of beating the market were no better than even. Why? Because only half the brokerage firms recommended stocks that beat the market.

As for possible sources of market inefficiency or ‘strategies for beating the market’, Shefrin falls back on the empirical evidence to find strategies to ‘beat the market’, i.e., “momentum investing, large cap, and growth”.

The discussion to this point is not designed to argue that behavioral finance makes little or no contribution to knowledge about financial activities. Rather, the primary objective of this section is to explore the potential for using behavioral finance to provide a theoretical rationale explaining how technical analysis can generate abnormal returns. Though there are explicit and implicit claims made by proponents of behavioral finance indicating that this would be the case, the process is largely inductive, working backward from empirical results to theoretical modeling. Behavioral finance is able to explain a wide range of alternative, possibly conflicting, hypotheses. Consider again the basic claim of behavioral finance: “heuristic-driven bias and framing effects cause market prices to deviate from fundamental values.” This could be consistent with pursuing a range of approaches to security analysis and investment strategy, from value investing to technical analysis to two fund separation. The result that security prices, particularly common stock prices, differ from fundamental values is commonplace. Providing insight into the psychological biases that can generate investment errors does not translate into advice about how, say, to identify specific securities that are mispriced.

The theoretical proposition that ‘security prices differ from fundamentals’ does not necessarily correspond to support for inefficiency. The test of inefficiency is the ability to generate abnormal returns using a given information set. This necessarily involves a joint hypothesis composed of the efficient market hypothesis (EMH) and the assumed return generating model. This complication permits believers in the EMH to claim that an empirical rejection of the EMH is actually a rejection of the return generating model. For example, if ‘abnormal’ returns are observed, as in the case of the small firm effect, it is possible to claim that the returns were not properly ‘risk adjusted’. If this is not possible, believers in the EMH can fall back on criticism of the statistical methodology, such

as data mining, data snooping, survivor bias, bid-ask bounce and so on, e.g., Sullivan et al. (1999), Haugen (1999b, ch.6). It is difficult to shake the assumption that individuals making financial decisions act rationally. This is an important source of attraction for behavioral finance. For positivists not wedded to the core beliefs of modern Finance, the subject provides a ‘rational’ explanation for irrational investor behavior.

Accepting that the various empirical results demonstrating ‘returns anomalies’ are correct, the number of possible theoretical explanations for such results is limited. A more-or-less complete list of possible explanations includes: institutional failure; information asymmetries; regulatory or institutional rigidities; psychological biases; and faulty interpretation of the statistical analysis. Of these explanations, psychological biases provide an attractive theoretical basis for return anomalies because the flexibility of this approach permits the explanation to be tailored to a specific anomaly. In addition, psychological explanations are adaptable to a range of historical and geographical situations that may not be possible with other types of explanations. This is particularly attractive when seeking a potential explanation for the profitability of technical analysis where the ‘chart patterns’ are seen as independent of the institutional context. However, the flexibility of behavioral finance is also a limitation as approaches capable of explaining a wide range of empirical results are also difficult to reject. Given these caveats, ***which of the psychological explanations is compatible with the potential profitability of technical analysis?***

Technical analysis is based on the notion that prices follow trends. As Edwards and Macgee (1966, p.6) observe:

prices move in trends and trends tend to continue until something happens to change the supply-demand balance. Such changes are usually detectable in the action of the market itself. Certain patterns or formations, levels or areas, appear on the charts which have a meaning, can be interpreted in terms of probable future trend developments. They are not infallible, it must be noted, but the odds are definitely in their favor. Time after time, as experience has amply proved, they are far more prescient than the best informed and most shrewd of statisticians.

If there are identifiable and predictable trends in prices, then this is evidence of market inefficiency. Some of the reported ‘return anomalies’ such as the January effect or the small firm effect as well as the profitability of buying winners and selling losers (or the reverse) could generate some types of identifiable trending in prices that are emphasized in technical analysis. However, as Edwards and Macgee claim, these return anomalies would be reflected in chart patterns: “[A technical analyst] could trade with profit in a stock knowing only its ticker symbol, completely ignorant of the company, the industry, what it manufactures or sells, or how it is capitalized. Needless to say, such practice is not recommended, but if your market technician is really experienced at his business he could, in theory, do exactly what he claims.”

If there is identifiable and predictable trending in prices, then why don’t rational individuals trade on the trends and generate sufficient price adjustment to eliminate the trends? In other words, if prices discount the future correctly, as technical analysts claim, then why are the trends not also discounted? Most adherents of technical analysis would answer this question by making reference to the struggle between bulls and bears – ‘heterogeneity’ in preferences, tastes and expectations in the terminology of modern Finance. This struggle determines the supply and demand for securities in the market. Recall from sec. 9.1 the theoretical outline for technical analysis given by Levy (1966): ‘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.’ Unlike in modern Finance, investor rationality is not a requirement for technical analysis. As such, behavioral finance has the potential to provide rational explanations for the potentially irrational behavior that is required to sustain technical analysis.

Is there any aspect of technical analysis that receives unambiguous support from behavioral finance? Put differently, which theory or theories in behavioral finance provides the strongest support for technical analysis? There are a number of candidates. According to adherents of technical analysis, the trends, and turning points in the trends, that do appear in prices require skill and experience to discern. This suggests that the behavioral theories aimed at over-reaction and under-reaction are most applicable. Shefrin (2000, p.85) summarizes the relevant empirical evidence:

The winner-loser effect is puzzling in that if winners and losers are defined in terms of one-year past returns, rather than three-year past returns, an underreaction effect emerges, not an overreaction effect ... What we seem to have is overreaction at very short horizons, say less than one month ... momentum possibly due to underreaction for horizons between three and twelve months ... and overreaction for periods longer than one year ... This phenomenon is quite complex, and does not lend itself to easy explanations.

It seems that skill and experience are also required to interpret the empirical evidence emanating from the New Finance. Following from the practice of technical analysis, it is also likely that if a viable combination of empirical explanation and behavioral theory is eventually identified, the feedback effect would either prevent detailed documentation of techniques that are successful or create preconditions for the combination to become unsuccessful once recognized by the market.

9.4 Relative Strength, Momentum and the Oscillator

A. Relative Strength

As discussed in sec. 1.3, modern Finance is firmly entrenched in the epistemology of logical positivism. Those instilled with this intellectual approach are compelled to develop theoretical models that are empirically tested on experimental data. (Hopefully such data is available.) Knowledge progresses 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.²⁴ This intellectual process has produced enormous strides in the natural sciences, where an immutable physical reality is the object of analysis. The gains achieved by logical positivism 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. Unlike modern Finance, the bulk of technical analysis proceeds by empirical observation. However, 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. Section 9.2 examined a range of these repeatable patterns: 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 (1996), though there are good reasons to make a distinction between the concepts. In an odd semantical twist, Wilder (1978) introduced a form of oscillator referred to as the “Relative Strength Index” that will be discussed below. 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. 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.

INSERT Figure 9-z GM and Ford and S&P 500

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, Figure 9-m compares the relative strength of GM, Ford and the S&P 500 using a one-year close-only chart. 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 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 indicator value for another stock relative to the S&P. Consider Figure 9-z, the indicator value around 1:30 EST on May 13, 2003 for Ford to the S&P is $(\$10.02/944.85) = .0106$, for GM to the S&P is $(\$36.61/944.85) = .03875$ and for Ford to GM is $(\$10.02/\$36.61) = .2734$. While it is possible to plot these individual series and use chart analysis 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 can 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 (see sec. 3.3). 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, p.609-10) 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?

B. Momentum and ‘Price Rate of Change’

In sec. 9.2, 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.²⁵ 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 are almost limitless.

Precisely when momentum entered the lexicon of technicians is unclear.²⁶ 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 practitioners and between academics and practitioners as to the definition of 'momentum'. For many practitioners, e.g., Schwager (1996), Blau (1995), 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, use conflicting definitions by defining 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.

INSERT Figure 9-n Momentum, 3,9 20 day

NOTE: Figure has 9n.mom.tif file only

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, $\{M(t,1)\}$. 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.

As illustrated in Figure 9-n, the difficulty of interpreting the momentum function may possibly be improved by taking larger differencing intervals to define momentum. Though the momentum charts for $\{M(t,3)\}$, $\{M(t,9)\}$ and $\{M(t,20)\}$ are still erratic, as the differencing interval is increased the

function becomes less erratic. 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 (see below). Casual inspection of the $M(t,20)$ chart reveals reasonably accurate trading signals at the minimum point around Dec. and a maximum in Feb., though the up move that begins in mid-March is missed. The use of specific differencing intervals is much like the choice of a sample length for a moving average, 100-day 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.

INSERT Figure 9-p The Momentum Ratio

NOTE: Figure only has 9p.mom2.tif file

In addition to increasing the length of the price difference, another potential method for dealing with the noisiness in $\{M(t,1)\}$ is to use price ratios. Using price ratios will not alter the shape of the momentum chart but will provide a scale that may be more interpretable. The price ratio technique can also be combined with lengthening the differencing interval. Examining Figure 9-p which provides $ROC(t,12)$ reveals that, as in Figure 9-n, a longer-than-daily interval between the prices results in a momentum chart that is similar, but not identical, to the original price chart. Figure 9-p also identifies **divergence** signals that can be associated with differing chart patterns, identified using trend lines, for the momentum chart and the price chart. Following Schwager (1996, p.527):

Bullish divergence occurs when a market makes a low, rallies, and then declines to a lower low, while [momentum] makes a low along with the market, rallies, and then fails to decline to a new low ... Bearish divergence occurs when a market makes a high, declines, and then rallies to a higher high, while [momentum] makes a high along with the market, declines, and then fails to rally to a new high.

These situations are indicated in Figure 9-p using trend lines. At point A, the higher highs on the price chart are not reflected by the ‘bearish divergence’ of momentum. Similarly at B, the lower lows are not supported by the ‘bullish divergence’ of momentum. The concept of divergence applies to oscillators, in general, not just momentum.

The difficulties of interpreting the erratic behavior of $(M(t,1))$ momentum illustrated in Figure 9-m have generated a large number of techniques designed to enhance interpretation of the momentum chart in order to improve the signaling potential. Specification and interpretation of these often complicated transformations of momentum differs across technical analysts. Casual inspection of Figure 9-m reveals a number of relevant issues. As discussed above, the scale of the price difference is in terms of prices with the momentum value fluctuating about zero. Because price is the scale, it is not immediately clear when a momentum value is ‘too high’ or ‘too low’. A small price change of, say, \$2 when the stock price is \$50 will appear to be the same on the momentum chart as when the price is \$10, when \$2 is a large price change. While there is no theoretical maximum, the lowest possible value is $-P(t)$. The scaling of a momentum chart depends on the definition selected. One difference associated with defining k day momentum as the ratio of prices k days apart is that the indicator will fluctuate around 1.00 with zero as an absolute lower bound, as indicated in Figure 9-p

that plots the momentum for $k = 12$ days. Using price ratios to define momentum does correct for the different impact of a \$2 change on a \$50 stock and a \$10 stock but the problem of defining when a momentum value is ‘too high’ or ‘too low’ still remains.

In conjunction with using bullish and bearish divergence signals, determining when a momentum chart generates a buy or sell signal typically can also be facilitated by specifying an upper or ‘overbought’ boundary and lower or ‘oversold’ boundary on the momentum function. As indicated in Figure 9-p, the divergence assessments were evaluated in the maximum and minimum regions of the momentum chart. As with divergence, the concepts of overbought and oversold are general oscillator concepts and are not restricted to momentum indicators. Yet, even if these boundaries can be determined from, say, the past history of the stock price momentum, the erratic pattern of momentum indicated in Figure 9-n indicates that it will be difficult to separate ‘false’ signals from correct signals. While it may be possible to widen the differencing interval, as in Figure 9-n, another natural approach is 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 $M(t, 1)$ (see end of chapter questions). 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**’.

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) and other modern Finance adherents that have examined ‘momentum strategies’, e.g., 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.²⁷

A number of academic studies have demonstrated the potential profitability of momentum strategies. The momentum differencing interval varies across studies, e.g., Jegadeesh and Titman use a six month interval while Chan et al. examine 5 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, 1.69) for the highest decile of equally weighted momentum portfolios down to the lowest decile portfolios (0.42, 0.46, 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.

C. Oscillators

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.”

The oscillator covers so many techniques that some technical analysis websites do not make any reference to the concept, e.g., 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 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 Figures 9-m to 9-p, 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 1950's, the fascination with the oscillator is a relatively recent development in technical analysis, gaining popularity starting in the early 1970's. 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.

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.

INSERT Figure 9-q MACD diagram
NOTE: Figure has only fig.9.q1.tif file

The DMA oscillator is a graphical representation of the dual moving average trading system that can be implemented directly on the price chart (see sec. 9.2). 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 an **MACD line** by subtracting a 26 period EMA from a 12 period EMA.²⁸ 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 Figure 9-q, it is conventional for MACD charts to also contain a histogram of the difference between the MACD line and the signal line. The histogram provides an oscillator-like chart that can be used to identify trades.

INSERT Figure 9-r MACD and Other Technical Indicators
NOTE: Figure has both .wpd and .tif files

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 (see Figure 9-r). 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 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 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, Figure 9-r also reports information on the stochastic.

As discussed previously, 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 and www.marketscreen.com.

QUESTIONS

1. Following Shefrin (2000, p.55-6), do the following exercise:

Imagine that a coin is being tossed 100 times. Write down the sequence of heads and tails that is *imagined* to occur as the coin is flipped. Repeat this exercise by actually flipping a coin 100 times and writing down the sequence of heads and tails that correspond to the order observed as the coin is flipped.

Compare the length of runs in the two sequences. What is the longest ‘run’ of heads and the longest ‘run’ of tails in the imagined sequence and in the actual sequence? What is the relative frequency of runs of five, four, three, two and one? What theory in behavioral finance would explain these

discrepancies?

2. Figure 9-f in sec. 9.2 provides two trend lines for the S&P 500, one associated with a 1 year price chart and the other with a 3 year chart. Which trend line is most appropriate to use in making an assessment of the long-term trend in the S&P 500? (Hint: consider where the last reversal in the S&P 500 occurred.) Does your answer depend on the type of trading strategy that is being pursued?

3. In sec. 9.2, the specification of a trading range involved resistance and support levels. Provide a practical explanation for trading ranges in terms of stop-loss orders and market-if-reached orders. Does this suggest that resistance and support levels for a trading range be defined in terms of a number of observations at the boundaries? (Hint: See Schwager 1996, p.73-7.) How would the activities of a stock exchange specialist affect the performance of a stock following a breakout?

4.a) An exponentially weighted moving average (*EMA*) has the form:

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

where $0 < \alpha < 1$. Prove that the *EMA* can be expressed as a infinite weighted moving average with weights $w_i = \alpha(1-\alpha)^i$. In other words:

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

b) 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 $T = (2 - \alpha) / \alpha$. Recognizing that simple moving averages weight each term in the moving average equally and that exponentially weighted moving averages have a declining weight scheme, specify conditions under which this mapping between a simple moving average and *EMA* make sense.

5. The following example of loss aversion is adapted from Kahneman and Tversky (1979). You currently own a stock that you purchased for \$10,000 and has fallen to \$2500. If you hold onto the stock there is a 75% chance the company will go bankrupt and the stock price will fall to zero, and there is a 25% chance the stock will recover to it's original value. Based on an intuitive inspection of this decision, should you sell the stock today and lock in a loss of -\$7500 or hold on? What is the expected value of the two transactions? Why does the decision to hold the stock reflect loss aversion?

6. In sec. 9.4, momentum was defined as $M(t,k) = P(t) - P(t-k)$. In sec. 9.2, the simple T day moving average $\bar{P}(t,T)$ was defined as: $\bar{P}(t,T) = \sum_{i=0}^{T-1} \frac{P(t-i)}{T}$. Setting $k = T$ what is the relationship between the momentum and moving average indicators? (Hint: Consider the case of $k = 5$. 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 $M(5) = \{\bar{P}(t, T) - \bar{P}(t-1, T)\} / 5$. More precisely,

show that in general for $k = T$:

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

Given this result, what is the relationship between a momentum oscillator and a dual moving average oscillator?

7. Blau (1995, p.13) makes the following statement: “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.*” Demonstrate the result that ‘the longer the duration of the moving average on momentum, the lower is the lag’ and the result (Blau 1995, p.14): “large moving averages of momentum ... have, in the limit, the exact *shape* of price.” (Hint: State the formula for an exponential moving average for price and substitute the formula of momentum for price.)

NOTES

1. The appearance of a chapter on technical analysis in a section on investment strategy may seem odd but, as discussed in chapter 10, market timing is an essential component of investment strategy. While applicable to both equity and fixed income security analysis, techniques of technical analysis are, arguably, more related to market timing strategies. If the speculative motivation for much of technical analysis is ignored, technical analysis is most appropriately discussed under ‘investment strategy’.

2. 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.

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

4. There are a number of sources that do pay some attention to the history. For example, Kaufman (1978, ch.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-1930's; the various systems developed by William Gann, starting in the mid-1930's and continuing until the 1950's; William Dunnigan, originator of “the thrust method”, during the early 1950's; Eugene Nofri, originator of the “congestion-phase system”; Chester Keltner, originator of the “minor trend rule”, during the late 1950's.

5. 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. As discussed in sec. 9.2, 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.”

6. While there are a significant number of technical analysts on Wall Street, the preponderance of analysts are of the fundamental persuasion.

7. 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”.

8. 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.”

9. As discussed in sec. 9.3, 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.

10. 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. 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, chap. 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.

11. 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 1930.

12. 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 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*.

13. The possibility of a substantive change in the Dow theory was recognized by Richard Russell in a interview published in *Barron's* on June 12, 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 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 1987 may have altered the underlying dynamics sufficiently to prevent a strong signal for the end of a bear market to emerge.

14. 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.

15. Observe that Figures 9-c and 9-e are for futures prices, where the underlying commodity is a security index. This highlights the close connection between technical analysis in the commodity derivative markets and in the "cash market" for stocks and bonds. 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. Standard drawing of trend lines applies to point and figure charts in the same fashion as bar charts and candlestick charts. In addition, Figures 9-c and 9-e are for futures prices. Because technical analysis is not limited to spot (cash) market trading, a number of important technical analysis sites are concerned with futures prices.

16. 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, p.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.

17. 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 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.”

18. 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 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.

19. 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. Oscillators are discussed in more detail in sec. 9.4.

20. 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 *Wall Street Week* with L. Rukeyser.

21. 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.”

22. Approaching the impact of psychological factors on financial and economic events from a positivist perspective is not original to behavioral finance. For example, the interaction between psychology and economics is explored in Katona (1951), an early precursor of behavioral economics.

23. The three themes of behavioral finance proposed by Shefrin (2000) are not the only possible classification scheme for the subject. For example, Statman (1995) proposes four factors for behavioral finance: prospect theory; susceptibility to cognitive errors; aversion to regret; and imperfect self-control. Fisher and Statman (1999) provide an illustrative application of these four factors to the time diversification puzzle (see sec. 10.4).

24. 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.

25. 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).

26. Bierovic (1996, ch.15 in Schwager 1996) observes that: “As early as the 1920's, 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.

27. Sec. 1.3 provided a general discussion of the rhetoric of Finance, identifying 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.

28. 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), Appel (1974).