ESSAYS ON TECHNICAL ANALYSIS IN FINANCIAL MARKETS

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Abstract

Technical analysis is the study of price movements in traded markets so as to forecast future movements or identify trading opportunities. Following a review of the history and research of technical analysis, three empirical chapters evaluate a number of propositions popular among technical analysts.

One approach used widely over the last century assumes that support and resistance levels can be predicted by projecting the ratios between the length and duration of successive trends, in particular using Fibonacci ratios like 1.618. This proposition is rejected for the Dow Jones Industrial Average by identifying turning points and testing for clustering by developing a block bootstrap procedure. A few significant ratios appear to support such anchoring by the market, but no more than would be expected by chance.

The thesis then reports a survey based experiment that tests whether individuals themselves do have an in-built tendency to anchor forecasts of future trends on previous trends. The significance of the survey results are tested using a novel kernel density estimator based bootstrap methodology. Respondents' forecasts do bear some relationship to the size of the most recent trend by certain whole-number ratios by more often than would be expected by chance.

The third experiment addresses the criticism that academic studies do not use a rich enough characterisation of technical analysis. 120 active market-timing strategies are tested using a regression based framework of equity fundamentals, macroeconomic fundamentals, behavioural variables and a diverse set of mainstream statistical indicators from technical analysis. Our recursive approach uses time-invariant rolling and expanding estimation windows as well as conditional windows based on the presence of structural breaks, identified using the conditional reverse ordered cusum method (ROC), of Pesaran and Timmermann (2002). Models that include both fundamental and technical indicators perform well, even allowing for realistic levels of transactions costs. And accounting for structural instability via the ROC method also improves performance.

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1. INTRODUCTION

The objective of this thesis is to evaluate a number of propositions popular among technical analysts. Technical analysis is the study of price movements in traded markets so as to forecast future movements and/or identify profitable risk:reward trading opportunities. When engaging in technical analysis analysts primarily use information generated by the marketplace such as:

- Past and present traded prices
- Liquidity
- Volume
- Open interest
- CFTC Commission Commitment of Traders (COT) Report
- Market depth e.g. Nasdaq Level II data
- Equity short interest
- Put : call ratios
- NYSE Odd-lots

This study of market-determined statistics contrasts with the study of fundamental information, which would also consider the drivers of prices such as news about economic statistics, company earnings and so on. The tools of technical analysis are visual, with turning points identified from patterns in charts of price movements and indicators derived from price or volume data. Usually this process is judgmental and not based on a statistical model of price movements. The rationale for technical analysis is that prices are not driven by a single underlying data generation process, but by market psychology which is episodic but leaves distinctive patterns in prices, perhaps through the channels of fundamental news flow (Neely, 1997) and order-flow (Osler 2001 and 2002). The same technical analysis techniques are applied to foreign exchange, metals, agricultural commodities, energy commodities, indices, equities, debt instruments and derivatives serving all these markets (Murphy, 2000). Many techniques are applied at all data frequencies from intraday through daily, weekly and monthly data right up to analysis of very long term waves in market activity.

Technical analysis is popular. It is used as a primary or secondary method of forecasting market trends by ninety per cent of participants in the foreign exchange market, the largest traded market according to the surveys of Allen and Taylor (1992) and Lui and Mole (1998), in London and Hong Kong respectively. Moreover, a quarter to a third of all currency traders rely on technical techniques exclusively (Cheung and Chinn, 1999; Cheung and Wong, 1999). Similar figures do not exist for the equity markets, but Internet search engine results are supportive of its use. Google yielded 1,540,000 hits for "technical analysis stock market," as compared to only 471,000 for "fundamental analysis stock market" or 345,000 for "fundamentals stock market."

Chapter 2 introduces the concept and history of technical analysis and surveys the academic literature in this area. Academic interest in technical analysis is growing. This has been stimulated partly by the emergence of "Behavioural Finance" as an alternative paradigm to "Efficient Markets Theory" (that left no room for time series based forecasting methods, technical or fundamental). Interest in technical analysis has also grown because improved computing power, databases and testing methodologies have made it possible to identify and test the significance of chart patterns. However, there remains a large gulf between the literature and industry practice, and the three studies in this thesis aim in different ways to help bridge that gulf.

There is for example a widespread belief in financial markets that trends in prices are arrested at support and resistance levels that are to some degree predictable from the past behaviour of the price series. Specifically, many market participants believe that ratios of the length and duration of successive price cluster around "round fractions" like ½ or 1, or Fibonacci ratios like 1.618. Chapter 3 of the thesis tests whether this is really true of movements in the Dow Jones Industrial Average. The concept of anchoring is in itself not new (see Tversky and Kahneman, 1974) and nor is the idea that forecasters base judgemental forecasts on patterns in preceding data. Yet this phenomenon has been neither documented nor tested in the literature. This thesis distinguishes the proposition from other forms of time-series anchoring with the term *proportional phase anchoring.* Objectively identifying turning points in financial time series is of central importance when evaluating many tools used by technicians. The chapter thus documents a number of approaches to identifying turning points in a time series. Turning points are identified by heuristics similar to those used in business cycle analysis, and test for clustering by developing a block bootstrap procedure. A few significant ratios appear, but no more than would be expected by chance given the large number of tests conducted, so we reject the proposition that proportional phase anchoring occurs in the aggregate US market index.

The idea that proportional phase anchoring might exist depends on market participants holding definite views about the "right" amount of recovery that the price of a share, say, might exhibit when recovering from a recent down-trend. Chapter 4 reported the results of an experiment designed to see if people do have an in-built tendency to prefer certain price targets over others. The significance of the survey results are tested using a novel KDE bootstrap methodology. This finds that respondents' forecasts of future turning points do bear some relationship to the size of the most recent trend, and that certain whole-number ratios (for example the idea that prices will recover by 1/2 of the most recent downtrend) occur more often than would be expected by chance. Interestingly, the format of series presentation does influence this kind of judgment. It is observed when the data are presented as charts, but not when the data are presented as simple numbers, in non-graphical form. This suggests that people apply a kind of visual aesthetic to the question of what is a "right" amount of price recovery.

The final study, reported in Chapter 5, is more conventional in design. It tests 120 active market-timing strategies using equity fundamentals, macroeconomic fundamentals, behavioural variables and mainstream indicators from technical analysis. Previous literature has not integrated behavioural or technical indicators into a regression-based framework for forecasting and trading. Investors' "real-time" trading decisions are simulated through recursive forecasting of excess returns from the Standard and Poors 500. Our recursive approach uses time-invariant rolling and expanding estimation windows. As noted above, technical analysts (and indeed efficient markets theorists) believe that any structure in the process driving market prices is temporary. The selected methodology is therefore careful to test for the presence of structural breaks, using the conditional reverse ordered cusum method (ROC), of Pesaran and Timmermann (2002). We find that models that include both fundamental and technical indicators perform well, even allowing for realistic levels of transactions costs. Using technical indicators alongside fundamentals improves performance. And accounting for structural instability via the ROC method also improves performance. However, model selection can be very different depending on whether the criterion used is model fit, predictive accuracy, returns, or risk-adjusted returns.

Chapter 6 reflects on the thesis and summarises the results of our work and considers avenues for future research.

2. TECHNICAL ANALYSIS: A SURVEY

There are many different mainstream technical analysis tools that are used by practitioners, described in standard industry texts such as Pring, 1998, Achelis, 2000, Murphy, 2000 and Edwards and Magee, 2001. These vary from easily replicable statistical indicators such as moving averages of prices, through support and resistance levels based on recent troughs and peaks in prices, to more subjective reversal patterns like "double tops", and even more nebulous sequences of "waves". Some of these indicators have a clear theoretical underpinning. The crossover of a price and a moving average of past prices will anticipate a turning point of an underlying price series that consists of a regular cycle plus noise. Other concepts like Elliott Waves and Fibonacci numbers are more esoteric. There is a growing academic literature, but this is mainly focussed on statistical indicators, and many commonly used approaches have not had the benefit of any academic attention. It is this very lack of academic exposure in the face of practitioner usage over at least one hundred years that provides our research imperative.

Examining the literature's coverage of technical analysis highlights that substantive shortfalls exist. Whilst this alone does not necessarily suggest any worth, practitioners' texts on technical analysis cover a wide range of tools of which the academic literature seems unaware. Furthermore, the existing literature often assumes it is assessing the entire body of knowledge of technical analysis by examining single aspects of it – or is interpreted as such. Unrealistically simple mechanical rules employed by the existing literature often constitute a "poor caricature" (Batchelor and Kwan, 2003) of practical technical analysis. It is wrongly asserted by the literature that technical analysis is used exclusively for short-time horizons (for example Neely, 1997) – this is not correct. Frequencies ranging from intra-day tick data to monthly or even quarterly data are in fact used (Achelis, 2000, Gann, 1949, Pring, 1998, Edwards and Magee, 2001 and Murphy, 2000). The likelihood that an analyst will also consider fundamental data of a security will necessarily increase as their time horizon increases. The cumulative conclusion is that it strongly appears that there has been little appreciation of what it is a technical analyst actually does and what they believe to be important. It certainly does not help that industry textbooks can only provide stylised examples of analysis outwith the context of practical application.

2.1. THE HISTORY AND DEVELOPMENT OF TECHNICAL ANALYSIS

The lineage of technical analytical techniques stretches back at least several hundred years. The first futures markets were born in Japan in the 1600s to redistribute the risk related to the production and distribution of rice. At the Dojima and Sakata exchanges' speculative culture embedded itself in Japanese culture, the candlestick method of representing rice markets evolved, most notably codified and successfully applied during the mid-1700s by Munehisa Sokyu Homma (1724 – 1803). Homma's success was legend, to the extent that songs were composed and sung about his trades and after becoming a financial consultant to the government he was granted the honorary title of Samurai. Whilst a highly respected field domestically, Japanese technical analysis evolved in a relative vacuum into a distinct form of pattern analysis with little dialogue between these and western techniques until the early 1990s (Nison, 1991 and Hirter, 2003). Other techniques to have been less successful in penetrating the west include Kagi, Rennko and Ichimoku Kinko Hyo (Nison, 1994).

During the first half of the twentieth century Dow Theory was recognised as the codified underpinning of much of western technical analysis. Charles Dow developed the theory, writing editorials on the subject in The Wall Street Journal, of which he was both part owner and editor, up until his death in 1902. To implement his theories of self-similar trend waves and of confirmatory trends between market indices, he developed the Rail (now Transportation) and Industrial Averages that bear his name and that of his partner Edward Jones. Whilst credit is given to Dow, the codification of Dow Theory was performed by others. Nelson (1902) first used the term "Dow Theory," refining the theory into its modern form, along side the work of William Hamilton's editorials in The Wall Street Journal between 1902 and 1929 and Hamilton (1922). Robert Rhea (1932) further distilled Dow's and Hamilton's editorials into a series of assumptions and theorems. Schabacker (1932) and Gartley (1935) are taken as seminal texts that further the work of technical analysis, culminating in Edwards and Magee (2001), this eighth edition revising the original 1950s text. R.N. Elliot's esoteric 1940s work on his wave theory (Prechter and Frost, 2000) extended Dow Theory's notion of primary, secondary and tertiary trends within a framework of proportionality between defined behavioural market phases. W.D. Gann (1942 and 1949)'s work provided additional perspectives in terms of trend analysis, proportionality and cyclicality. Other than Lefèvre (1923) and Livermore (1940), both chronicling the trading discipline of one of the early twentieth century's most renowned traders, other technical analysis related texts pre-dating WWII are either rarely used or have quite simply not stood the test of time amongst practitioners.

Murphy (2000) is seen as the modern touchstone of stylised technical analysis.

Achelis (2000) is often referred to as an overarching reference for the techniques above, and for statistically determined technical indicators developed over the past half a century. It is in this area, outwith the realms of chart-reading, that the most recent developments in technical analysis have arisen. Technical indicators include trend analysis indicators such as simple or exponential moving averages (Murphy, 2000), Appel (1985)'s moving average convergence/divergence (MACD) or Wilder (1978)'s Average Directional Index (ADX). Oscillators attempt to quantify cyclical oscillations and include moving average oscillators (Murphy, 2000), the Directional Movement Index (DMI) (Wilder, 1978) or the Relative Strength Index (RSI) (Wilder, 1978) – not to be confused with relative strength analysis of the ratio between two time-series. George Lane's inappropriately named Stochastic Oscillator was developed in 1948, extending the notion of oscillation to consider the relationship between daily closing prices and intra-day extreme highs and lows (Lane, 1984a, Lane, 1984b and Myers, 1998).

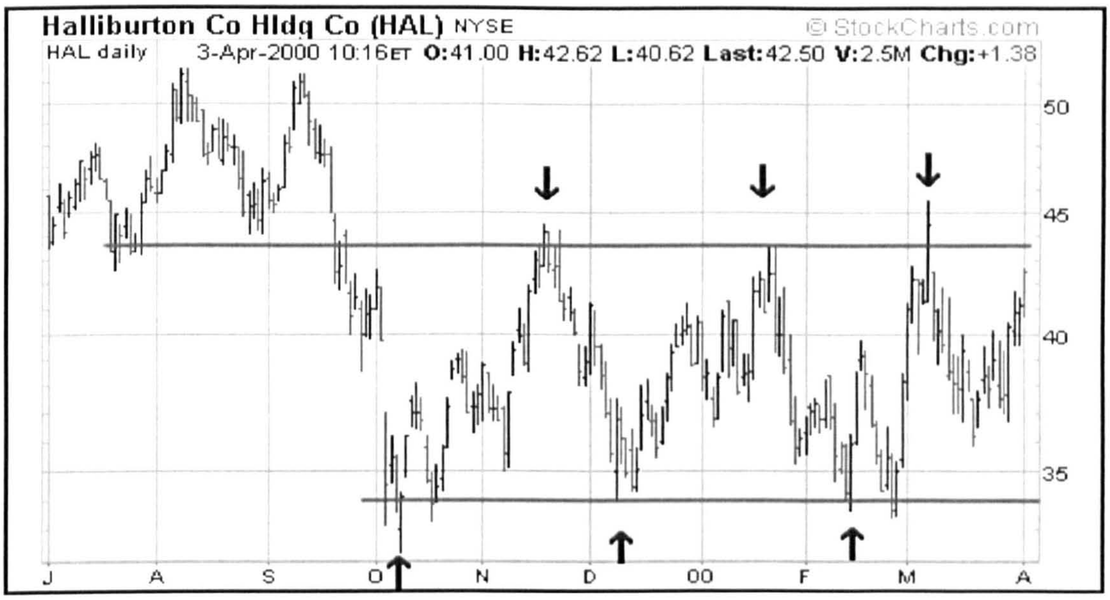
2.2. SUPPORT AND RESISTANCE LEVELS

As Pagan and Sossounov (2003) point out, time series of cumulative financial returns do not move in straight lines but in series of cyclical phases divided by peaks and troughs. The meaning of support and resistance levels is something that is implicitly clear and understood between market participants that use technical analysis. The often-cited standard definition is that support (resistance) exists at a price level where demand (supply) is sufficient to cause an at least temporary interruption of a downward (upward) move. The persistent resistance at the 1,000 level on the Dow Jones Industrials for a twenty year period starting in the early 1960s is often cited and provides a vivid textbook example (Figure 2-1).

Figure 2-1 – DJ-30 Long Term Trading Range (1960s-1980s)

Analysts normally identify levels subjectively by examining previous turning points. Technical analysis also states that support becomes resistance, and vice versa, once that level is broken. This provides one of the strategies that technicians follow for stop-loss order placement to enter or exit positions. Nevertheless, technical analysts observe that levels may not be precise and that volatility could briefly drive prices beyond zones of support or resistance whilst maintaining these zones (Figure 2-2).

Figure 2-2 – Support and Resistance Levels



The academic literature caters for this with the use of thresholds around levels, although these appear to have little effect on results (Osler, 2000).

The idea of there being a concentration of supply or demand at specific price levels has been an inherited lore for practitioners for a century or two. Yet this is not entirely self-evident in modern financial theory. Technical analysis textbooks claim that support and resistance levels come from a systemic order flow effect at the prices of previous extremes. Furthermore, they assume that stop and limit orders cluster around these previous turning points and prices cascade when the levels are breached. Rosenberg and Shatz (1995) specifically advocate referring to technical analysis with more effort behind such economic explanations; yet the general financial literature has been sceptical of any notion of concentrated order-flow.

Existing analyses suggests that stop-loss orders are not rational (Dybvig, 1982), yet the industry literature shows that market participants have used them to impose self-discipline to avoid the disposition effect for at least a century. Moreover, Osler (2001) points out that the assumptions of the standard models are not satisfied: price slippage means that trading is not frictionless and information imperfections do exist between market participants. Relevant information is overwhelming, even for those who can give their full attention to market news. A bank's order book constitutes private information that can be used to improve forecasts and improve risk management. Offsetting stop orders at identical prices demonstrates that agents are in fact heterogeneous in their utility functions and beliefs. If that were not enough to place doubt in one's mind, institutional factors also turn out to be relevant in price discovery – quotation conventions are shown to have a measurable influence upon exchange rates. Osler (2001)'s critique showed that the assumptions underlying many models are in fact so tenuous that conclusions drawn from them against an order-flow hypotheses may be just as tenuous. Goodhart and Payne (1996), Osler (1998), Evans and Lyons (1999), Rime (2000), Lyons (2001), and Evans (2001) all suggest that order-flow is pivotal in defining short-run currency movements.

Osler (2001 and 2002) takes a micro-structural approach to explain the success of familiar technical predictions: the triggering of stop-loss driven price cascades. Foreign exchange literature suggests that news flow can indeed be secondary to order-flow in driving exchange price movements (Cai, Jun, Yan-Leung, Lee and Melvin, 2001 and Evans, 2001). Osler's thesis, however, is not that stop-loss orders are the sole or principal cause of extreme forex moves. Her thesis is that when stop-loss orders cascade, other factors are often involved as well e.g. currency crises, intervention, news, etc. There are nevertheless also events where rational, yet uninformed investors, could accentuate cascades by trading with triggered stop-losses, thinking that they reflected genuine information flow (Osler, 2002).

Osler (2001) studied 9,700 currency stop-orders from an institutional forex stop-order book across nearly seven and half months. These included stop-losses, which close positions to minimise losses, and profit-stop orders, which liquidate all or part of profitable positions. A statistically significant asymmetry in the distribution of stop-loss orders was found at round numbers when compared to fairly symmetric distribution of profit-stop orders. Stops-losses tended to be placed just below (above) round numbers or support (resistance) and orders to take profits are at round numbers or support (resistance) – consistent with trading axioms. This must be at least partially self-fulfilling, as the actions of others in placing their stops in this manner could make it rational for others to do so. Yet this is not a conclusive point, as Osler (2001) points out; clustering at such levels will have had reasons for starting in the first place. Osler (2002) takes this notion of examining price cascades through concentrated order levels further, arguing that these may explain the economic rationale behind forex returns' "fat-tails." Stop-losses clearly provided positive feedback into a trend generating price cascades, whilst negative feedback from profit-stop order does not cause cascades. Osler (2002) does stress that the idea that stop-loss orders contribute to price cascades is not original and is embedded industry lore. Such work has uncovered similar results in the equity market. Limit book cumulative depth on the NYSE limit book is cointegrated with support and resistance levels (Kavajecz and Odders-White, 2004). The previous price level: liquidity relationship was high and a finding consistent with Osler (2001)'s trend reversal findings in the currency markets.

An understanding of the microstructural factors behind levels is important, but this is distinct from examining analysts' predictions of significant levels. Osler (2000) provides the benchmark assessment. Price reaction to published levels is compared to the reaction to 10,000 randomly chosen levels using a bootstrap procedure. An exchange rate was defined as having hit one of these support (resistance) levels if the bid (ask) price fell (rose) to within a 0.01 threshold of that level. The trend was defined as interrupted if the bid (ask) exceeded (fell below) support (resistance) fifteen minutes later. To compensate for the arbitrary nature of these values, 0.00 and 0.02 thresholds and a thirty-minute interruption filter were also used, making little difference to the results. An interval of 15 minutes was settled upon by the time of Osler (2002) on the basis of the analysis of Yao (1997). Yao found that prices sustained their response to a trade for approximately sixteen minutes (the product of the average four minutes between passive trade times and the five-trade time interval for the maximum price impact). Significant forecasting ability was for all 16 firms: currency pairs, with some firms performing better than others. Round numbers did constitute a large proportion of the published levels (a phenomenon reconfirmed in Osler, 2001 and Batchelor and Kwan, 2003). The industry belief regarding "range trading" was also empirically supported by the finding that the number of statistically significant levels increased when volatility was lower, as markets were range bound rather than trending. Osler (2000)'s place in the literature is central as it involves the anticipation of bounces in time-series, rather than continuations in a trend (as found in Brock, Lakonishok and LeBaron (1992), Curcio, Guillaume, Goodhart and Payne, 1997 and Sullivan, White and Timmermann 1999). Moreover the levels were created by market participants and on a high frequency basis.

Nevertheless, a key weakness is that the published levels were not classified by the techniques used to determine the levels. Possible techniques include subjectively or objectively identified prior turning points, price retracements or projections, divergence between technical indicators and price trends, technical trendlines and trend channels. Osler did acknowledge this in pointing out that the published levels came from a variety of different methods. Each of these approaches is distinct in approach and analyst preference.

There are also a number of papers that examine stylised, systematic trading approaches based on breakouts through levels. Whilst a clearly related literature, it must be distinguished from the above work; trading systems are concerned with systemic trading decisions rather than understanding the underlying phenomenon. Brock *et al* (1992)'s found statistically significant forecasting ability in the Dow Jones Industrial Average using a channel-breakout system to generate a buy (sell) signal on breaks of the local maximum (minimum) over a specified period. Conditional empirical returns were significantly greater than trades on simulated series. These results potentially stem from the order-flow price cascade thesis of Osler (2001 and 2002) but methodological weaknesses do exist. Transaction costs were not accommodated for in this study and data-snooping risks were revealed by Sullivan *et al* (1999)'s re-examination. They used a different bootstrap methodology to correct for the effects of data-snooping to evaluate whether superior performance came from "superior economic content, or just due to luck." This risk of survivorship bias within the remaining rules still used in practice was balanced by a universe of around eight thousand parameterisations of trading rules. These were applied also to the Dow

Jones Industrial Average over the same period as Brock *et al* (1992), plus an out-of-sample test over the following ten years. As per Brock *et al*, from 1897 to 1996 some of the rules were profitable, even after adjustments for data snooping were made. Yet even the best performing rule was not profitable out-of-sample.

Interesting questions remain from this literature; a key point of Brock *et al* (1992) still stands after Sullivan *et al* (1999). Their returns were not consistent with either the random walk, the AR(1), GARCH-M or Exponential GARCH models. Moreover, predictive levels were not dependent on central bank intervention (Osler, 2000 and 2002 versus LeBaron, 1996). Even where there is strong correlation this is not necessarily causation (Neely, 2000) and intervention may often be caused by the exchange rate moves that precede them (Osler, 2001). It is also unlikely that chaotic processes were responsible, as these are independent of the round numbers that dominate published levels (Osler, 2000, 2001, 2002 and Batchelor and Kwan, 2003).

2.3. CHART PATTERNS

The technician's definition of a bull trend is series of higher peaks and troughs, and consecutively lower extremes in a bear trend. They believe that chart patterns are deviations from this definition of a trend and have a systematic effect. The textbook theory is that patterns are based on the notion of price cascades following these deviations from trending extremes. Chart patterns can by separated into reversal patterns and continuation patterns. Reversal patterns have been the dominant focus of the academic patterns literature and occur at trend reversals. Whilst reversal patterns form the basis of at least temporary trend reversals, continuation patterns analyse confirmation of and continuation of a pre-existing trend via price cascades (as per

Osler 2001 and 2002). The frequency of data that a pattern forms within determines its importance. A reversal pattern formed on a chart with a five-minute frequency is not likely to be interpreted as having long-term implications, for example.

The head and shoulders pattern is perhaps one of the best known chart patterns, also amongst those who are not familiar with how investors use technical analysis. Head and shoulders are also seen as major reversal patterns that form after an extended trend. The textbook rationale is the initial disappointment in the market when the third peak does not break the resistance at the second peak and forms a lower high. The pattern is made up of two peaks at a similar price level separated by a peak at a higher level. The two troughs prior to the breakout through these lows are at a similar level. The second peak marks the highest point of the current trend; the current trend does not appear in jeopardy at this time. The following trough is not higher than the previous, placing the current trend under question, but not yet invalidating the trend by forming a lower low. The following peak is substantially lower than the last, perhaps only meeting the approximate level of the penultimate peak, again placing the trend at risk. This two-stage warning comes from the technicians' definition of a clear trend in a market, a series of higher peaks and troughs. The trend reversal is confirmed by the break of support triggering the pattern and volume would be expected to expand on up swings and contract on down swings. The pattern is completely reversed for the bullish head and shoulders bottom patterns.

Figure 2-3 – Head and Shoulders Top

Levy (1971) provides a relatively early example of the few examinations of chart patterns. This examined 9,383 long/short signals from thirty-two combinations of what it termed "five point patterns" across 548 NYSE stocks over five years. The findings were that "neither the best nor the worst (patterns) performed very differently from the market." After accounting for commissions no patterns were profitable. Interestingly, the most bullish patterns identified by Levy were textbook bearish patterns. After an interlude of nearly thirty years, Lo, Mayansky and Wang (2000) examined a range of chart patterns. They examined ten different textbook reversal patterns, which contrast with continuation patterns during pauses in a trend (see Leigh, Modani, Purvis and Robert, 2002 and Leigh, Paz and Purvis, 2002). Patterns were identified after smoothing the series using kernel regressions. Comparing the unconditional return distribution to the conditional distributions revealed that several chart patterns provided incremental information over a 31-year sample period. These patterns also occurred around turning points more often than would be expected by chance. Lo *et al* do not comment on whether this can be translated into a profitable mechanical trading strategy. Jegadeesh (2000) questioned whether the patterns found could indeed be traded – the standardised means were "remarkably close to zero" and none of the *t*-statistics were reliably different from zero. Jegadeesh also highlights the subjectivity in Lo *et al*'s systemisation of chart patterns (the actual pattern definitions, choice of smoothing technique and smoothing parameterisation), but accepts that it is unavoidable. Interestingly, the increased recognition of patterns after Lo *et al*'s consultations with practitioners was not seen as important by Jegadeesh *a priori*. The assumption was the statistically optimal bandwidths for the kernel regressions would suffice, yet a 30% reduction of the smoothing window followed these consultations. This is of interest because practitioners would see the sensitivity of the turning point dating as important *a priori*.

The remaining chart pattern literature focuses on the best-known chart pattern, the head and shoulders pattern. Yet the literature does not explain the technicians' rationale for this pattern – a three-stage interruption of the sequence of higher (lower) lows and highs that form a technical up (down) trend. Put otherwise, a head and shoulders pattern combines "smoothed trends, peak-and-trough-progression patterns, resistance levels, volatility clustering, time limits and trend reversal patterns" (Lucke, 2000 p.2). It is clear that even the limited conclusions of Lo *et al* (2000) are not uncontested facts. Research performed at the Federal Reserve Bank of New York did conclude that the head and shoulders pattern was "not just some flaky pattern" (Osler and Chang, 1995). Yet the controversy is aptly represented with the later renaming of the published paper, referring to instead to "methodical madness" (Osler and Chang, 1999). Six currencies were examined across twenty-one years of daily closing prices.

Predictive power existed for the pattern in two out of four currencies examined. When adjusted for transaction costs, interest rate differentials or risk, profits in the yen and mark remained "substantial." Moreover speculation in all six currencies would have been both statistically and economically significant, yet the minimum textbook returns did fail 78% of time. These results were robust to the algorithm's parameterisation, the sample period and assuming GARCH driven returns rather than a random walk. Nevertheless, the pattern was inefficient – it was dominated by simpler forex trading rules. Application in the equity markets has been even more critical. The pattern was found to be unprofitable for 100 firms chosen randomly from CRSP database (Osler, 1998), even though there was systematic activity revealed by a significant increase in volume following the pattern.

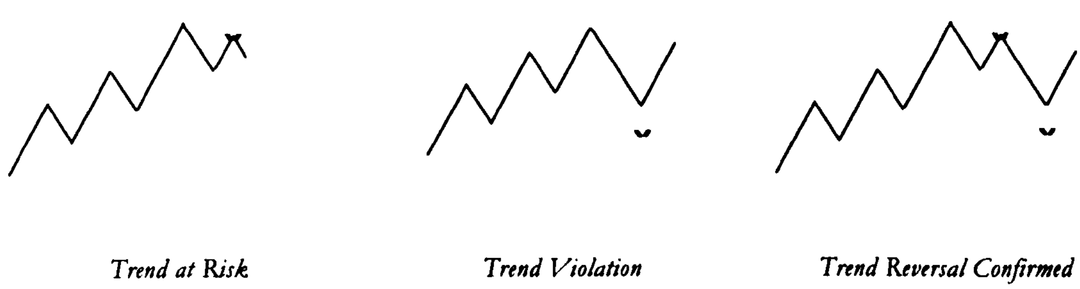
Bulkowski (2000) must be highlighted only because it is a rare practitioners' attempt to evaluate a number of chart patterns systematically. It finds generally supportive evidence across a large number patterns and variations. Whilst more rigorous than the majority of textbooks, it does not give an academic level of methodological detail. As a result Bulkowski's results must be balanced with its lack of methodological transparency.

2.4. WAVE THEORIES

DOW THEORY

Dow Theory is important both as the primary foundation of western technical analysis and as an early discourse on the nature and duration of long-term equity trends, with their guidelines parameterising Pagan and Sossounov (2003)'s cycle dating model. The goal of Dow and Hamilton was to guide identification of the primary long-term trend and trade in that direction, rather than dictating precise trading decisions. Dow Theory is explicitly not intended for short-term trading. Hamilton (1922) stated that those who successfully applied Dow Theory would rarely make in excess of four or five trades annually, a range echoed by Gann (1942 and 1949)'s application of other longer term techniques. This must be contrasted with the general academic assumption that technical analysis is only used with short-time horizons (for example Neely, 1997). Dow Theory assumes that manipulation of the primary, long-term, trend is not possible and it must reflect trends in the underlying fundamentals as the "*averages discount everything*" (Hamilton, 1922). Whilst the unexpected will occur, it is usually only shorter-term trends that are affected according to Dow. Shorter-term trends, lasting hours or weeks, could also be subject to "manipulation" by institutions, speculation, news flow or rumours according to Hamilton. Hamilton believed that more highly capitalised equities were less open to "manipulation" and that it would be virtually impossible to directionally manipulate the market as a whole for any sustained period.

Figure 2-4 – Dow Theory: Trend Risk, Violation and Confirmation



It was Dow Theory that first codified the technicians' definition of a clear trend (Figure 2-4). A technical up (down) trend is defined by prices that form a series of rising (falling) peaks and troughs. An up (down) trend is considered at risk if a lower (higher) high (low) forms. An up (down) trend is considered as violated if a lower low (higher high) forms. These two notions are seen as particularly decisive if a lower high (higher low) is followed by a lower low (higher high). These are all deviations from the standard definition of a definite technical trend of higher (lower) highs and lows.

Dow and Hamilton stratified trends in the Dow Jones Industrial and Transportation Averages into primary movements interrupted by secondary movements. These are in turn constituted by tertiary day to day daily fluctuations. Primary moves are described as lasting from a few months to many years and reflect the broad trends of business conditions – the commentators' bull and bear markets. Although Hamilton gave general guidelines for the amplitude and duration of primary trends, he warned against using these as rules for forecasting what he saw as largely indeterminable. The primary trend in the market as a whole is traditionally determined by agreement in the individual trends of the Dow Jones Industrial and Transportation Averages. Hamilton arguing that activity would begin in the Rail Average before the Industrial Average. When Dow Theory was being developed at the turn of the last century the railroads were a vital link in the economy. The belief was that economic activity that was sufficient to drive long-term stock market trend would first have to show in the transportation of goods and raw materials – and hence the earnings and valuations of transportation companies. This underpinning definition of a trend is also applied to the secondary trends and daily fluctuations. Hamilton believed that secondary reactions defied the primary trend for several weeks to months and combated excessive speculation. Hamilton observed that secondary movements retrace 1/3 to 2/3 of the primary move, with 50% being the typical amount, and that these tend to be more volatile than the preceding primary move. Tertiary daily fluctuations are those trends that last a few hours to a few days, normally lasting less than a week. Dow Theory sees daily fluctuations as being individually untradable, unless forming an analysable chart pattern.

Rhea (1932) did emphasise that whilst Dow Theory gave volume a role in confirming the strength of an advances and identifying potential reversals, price action was the ultimate determinant.

Table 2-1 – Accumulation and Distribution Cycles (Hamilton, 1922, Wyckoff, 1924 and Soros, 1994)

Primary Bull Market **Stage 1 – Accumulation**	**Primary Bull Market** **Stage 2 - Sustained Trend**	**Primary Bull Market** **Stage 3 – Excess**
Hamilton saw that the first stage of a bull market as largely indistinguishable from the last reaction rally of a bear market. Stocks appear "cheap" but are not in demand. Patient value investors step in for the long haul. Stocks quietly firm up to widespread disbelief that a bull market has begun.	Hamilton considered this stage as the biggest, driven by improving fundamentals. Participation is fairly broad and trend followers begin to participate.	Hamilton construed this period as driven by excessive speculation and appearing inflationary pressures. Public involvement is widespread and extraordinarily confident, fuelling excessive valuations.
Primary Bear Market **Stage 1 – Distribution**	**Primary Bear Market** **Stage 2 - Sustained Trend**	**Primary Bear Market** **Stage 3 – Despair**
Informed investors begin to close positions, realising that fundamentals are not as previously thought. The public constitutes willing uninformed investors. Dow Theory sees the financial press as giving little to indicate a bear market and general business conditions remain good. Returns falter whilst very few forecasters or investors believe a bear market has started and most remain bullish. Hamilton noted that swift secondary reaction rallies during bear markets give false hopes to bullish sentiment.	As with the primary bull market, Hamilton saw this stage of a primary bear market as providing the largest move. This is when the trend has been identified as down and business conditions begin to deteriorate. Earnings estimates are reduced, shortfalls occur, profit margins shrink and revenues fall. As business conditions worsen, the sell-off continues.	All hope is lost and stock ownership is taboo. Valuations are now low, yet supply persists as market participants exit at all cost. Fundamentals remain bleak and are priced into stocks until complete, perhaps irrationally underpriced by this stage.

Hamilton identified three behavioural stages for both primary bull markets and primary bear markets, driven by cycles in accumulation and distribution of securities. These are shown in Table 2-1. These stages are analogous to the product life cycle model in marketing that has been extrapolated to the company-dividend life cycle. Wyckoff (1924) also expands upon this concept of accumulation and distribution cycles and Soros (1994) uses the same structure to understand market psychology.

Brown, Goetzmann and Kumar (1998) is apparently the only recent research of practitioner wave theory. They re-examine the seminal Cowles (1934) evaluation of Hamilton's 1902-1929 record. A neural network system was developed that incorporated rules for identifying the primary trend and was tested against a buy-and-hold approach for the period from 1929 to September 1998. The system switched between long positions in the equity market and fixed income securities. It was these fixed income periods that significantly reduced the volatility of the portfolio, central to both Dow Theory and modern portfolio management theory. Over the 70 year sample the system outperformed buy-and-hold by about 2% per annum, whilst also bearing less risk. It under-performed buy-and-hold during bull markets and outperformed during bear markets, as expected *a priori* of a lagging approach (Hamilton, 1922). As a result, the final 18 years of the sample, a prolonged bull period, showed the Dow Theory system under-performed by a margin of 2.6% per year. Nevertheless adjusting for risk means that the Dow Theory system still outperformed buy-and-hold over that 18-year period.

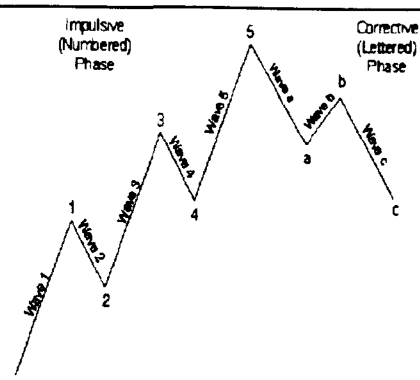
ELLIOTT WAVES

In the 1940s Ralph Nelson Elliott expanded upon Dow's belief that market trends exist within three distinct campaigns divided by two corrective moves. Whilst

Hamilton urged analysts not be overly rigid when conceptualising how markets work, Elliott Wave theory attempts to prescribe many facets of markets' trend or counter-trend states. Mandelbrot (1999) dismissed Elliott Wave theory outright in his examination of fractals and scaling in finance. This is because "wave counting" is perhaps the most extreme example of subjectivity in technical analysis and thus incredibly difficult to define or evaluate. An impressive number of interpretations are possible when identifying "Elliott wave counts". This is even despite the successful penetration of the principle in the finance industry. There have been a number of pieces of the software that tackle the issue (EWaves, Advanced GET, etc.), none of which usually agree on a wave count.

Elliott wave theory stretches Dow Theory within a framework of proportionality and definitive predefined market phases. These waves contain sub-waves that are meant to adhere to the same rules in a kind of self-similarity, in the fractal sense. These widely used principles incorporate proportionality into subjective identification of behavioural waves in markets. *Specific* waves are believed to be key proportions of *specific* preceding waves or pairs of waves. This same proportionality is claimed to apply to sub-waves or waves of a higher degree. This is believed to allow increased confidence in wave projections as higher degree wave projections would be supported by sub-waves' projections.

Figure 2-5 – Stylised Elliott Wave Advance and Correction



Several rules are outlined by Elliott (Prechter and Frost, 2000).

Wave 2 can never retrace more than 100% of Wave 1, i.e. the first correction (reaction) of an impulse wave must not exceed the start of the impulse wave.

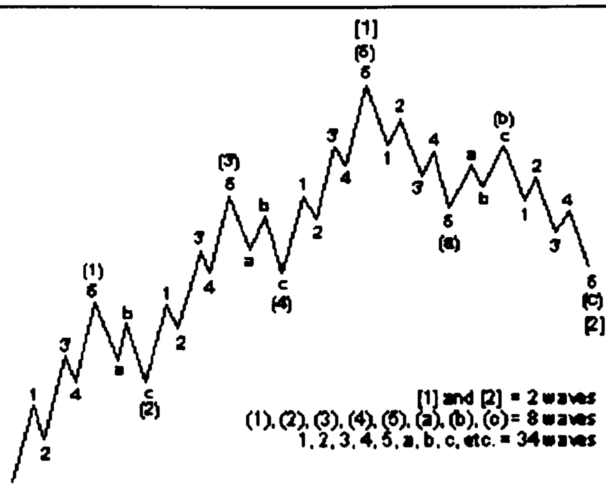
Wave 4 can never retrace more than 100% of Wave 3.

Wave 4 overlap can never overlap with Wave 1, i.e. the final correction of an impulse wave must never move into the price range constituting the first wave of the impulse. Practitioners do not always hold to this rule, particularly in commodity markets.

Wave counting often allows for Wave 4 to overlap into Wave 1, but no further than the level of Wave 2, support (resistance) at the end of an impulse wave's first correction (reaction). This is claimed as occurring particularly often if wave 1 is the extended (largest) wave of the five-wave impulse sequence.

Prechter and Frost (2000) provide the basis for the outline of Elliott Wave theory given below. We document only some of the detailed prescriptions. The level of subjectivity when labelling waves is clear from this, even when compared to chartism in general. Figure 2-5 illustrates the archetypal theory of "impulse waves" *in the direction of the trend* exist in a five-wave sequence. After an impulse five-wave sequence, a "corrective wave" *retraces the impulse wave.* Elliott Wave practitioners describe this corrective wave as an "ABC" or "zig-zag" pattern. Figure 2-5 also documents basic wave counting. As stated, Elliott Wave expands Dow Theory's self-similar trend paradigm, that of each trend being part of a greater trend and in turn composed of sub trends (Figure 2-6).

Figure 2-6 – Elliott Waves: Stylised Primary and Secondary Wave Structure



The primary two stage impulse– corrective pattern is identified by [1] and the [2]. The secondary trend's peaks and troughs are identified in brackets. Its subwaves, the tertiary trend, are identified without brackets. Notice that waves (1),(3),(5),(a) and (c) are all five stage impulse waves because they are in the direction of the higher degree trend, whether that is impulse or corrective. Similarly, waves (2), (4) and (b) are all three stage corrective waves.

Elliott Wave considers the occurrence of the Fibonacci series as having a pivotal influence – 1, 2, 3, 5, 8, 13, 21, 34, 55, 89, 144, etc., with each number being the sum of the last two. In the context of waves and their sub-waves, the number of waves within the stylised self-similar outline in Figure 2-6 increases along the Fibonacci series as one subdivides the waves (Table 2-2).

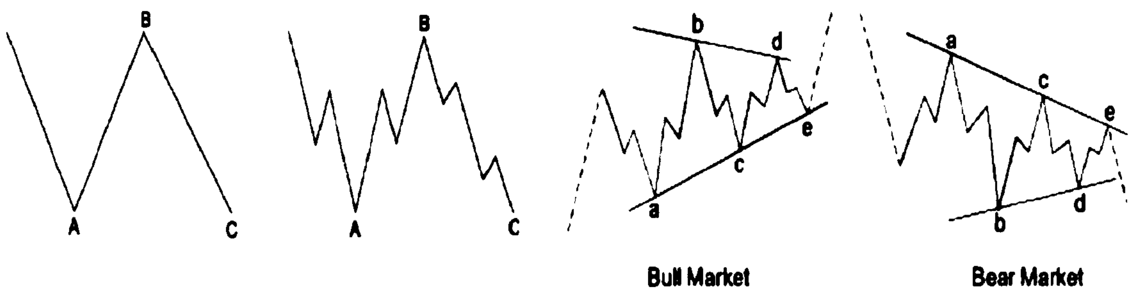
Table 2-2 – Fibonacci Progression of Self-Similar Elliott Waves

Degree	**Waves on Figure 2-6**	**Number of waves constituting Wave [1]**		**Number of waves constituting Wave [2]**		**Total constituting Waves [1] and [2]**
Largest waves	[1] and [2]	1	+	1	=	2
Sub-divided	(1)...(5) and (a)...(c)	5	+	3	=	8
Further sub-divided	1...5 and a...c	21	+	13	=	34
Further sub-divided	Not marked	89	+	55	=	144

The progression of the total number of waves and the number of sub-waves constituting Wave [1] and Wave [2] separately all increase along the series, omitting two Fibonacci numbers each time. This stylised process of sub-dividing to a smaller degree continues indefinitely until such time that the timeframe concerned does not maintain a perceived wave structure.

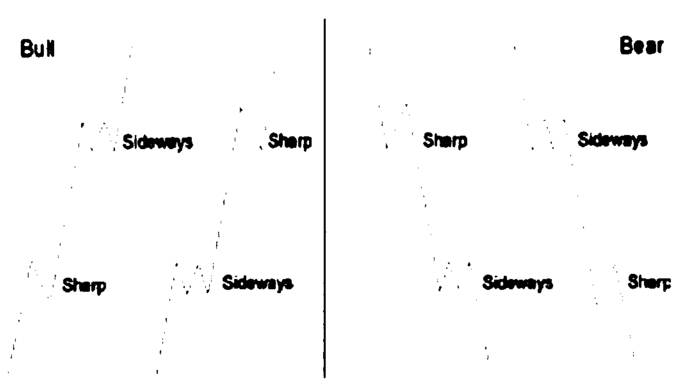
Whilst Elliott Wave theory identifies impulse waves as only having five waves, it has identified other corrective patterns over and above the three-stage (5-3-5) "ABC" pattern above (Figure 2-7). A "simple" correction, such as an "ABC" pattern, would be expected to be followed by a "complex" pattern such as a triangle (Figure 2-8).

Figure 2-7 – Elliott Waves: Flat and Triangle Correction/Consolidations



Flat Correction *Triangle Corrections*

Figure 2-8 – Elliott Wave: Principle of Alternation

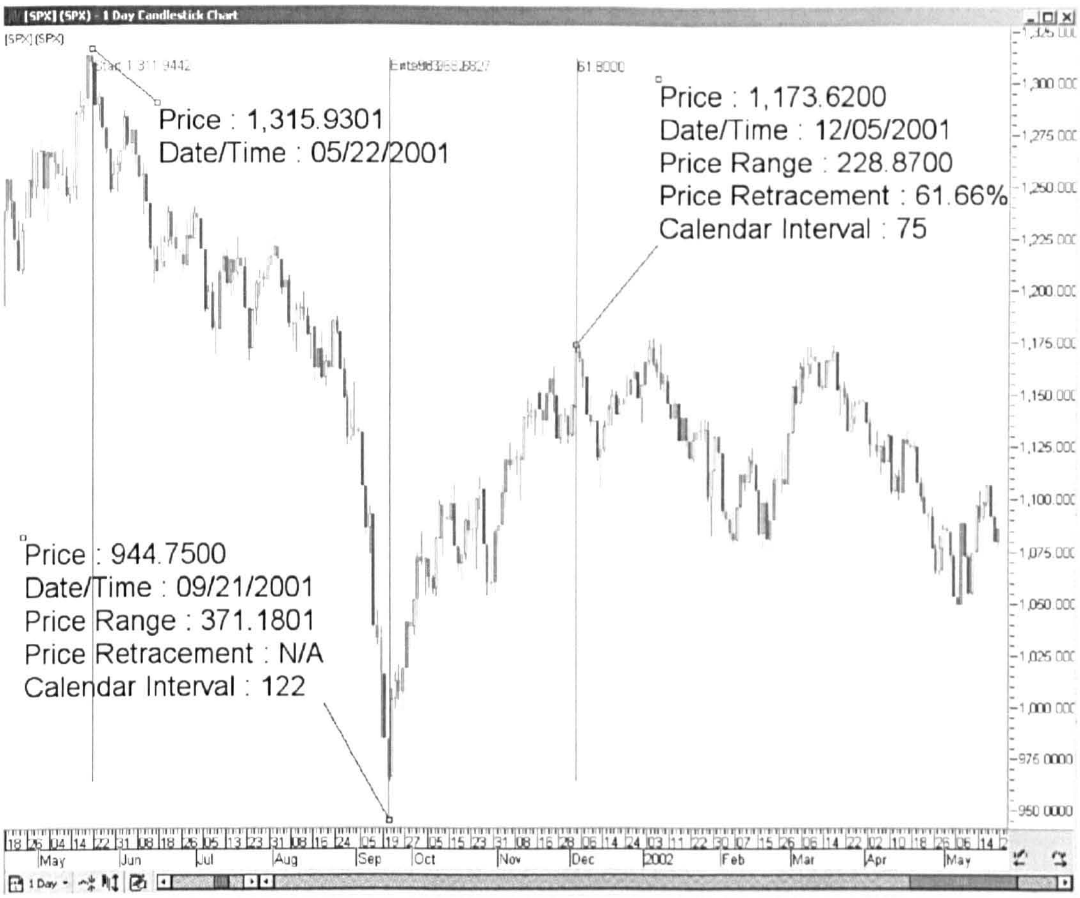


PROPORTIONAL PHASE ANCHORING

As aforementioned in the context of Dow Theory, Hamilton (1922) observed that market corrections roughly retraced 33% to 66% of a primary trend, with 50% being the typical price retracement. These price retracements are measured by analysts, measuring the percentage that prices have retraced from the high to the low. For example, if a stock moves from a low of 50 to a high of 100 and then retraces to 75, this 25 point move would have retraced 50% of the original move from 50 to 100. Elliott wave analysts have specific prescriptions for the proportions between specific phases. Nevertheless, a greater number of technicians look at proportionality generally, regardless of any wave counting "structure" as per Hamilton. Measuring price retracements is believed to be helpful in determining price levels/ranges at which prices may reverse and continue their prior trend. Furthermore, bull (bear) trend phases are often asserted as being proportional to previous bull (bear) phases. Analysts often combine multiple retracement levels with projected levels, support, resistance, pattern analysis or indicator analysis. The same analogy is applied to the proportion of the time spent in those trends e.g. bull trend phases would be proportional in their duration to previous bull phases.

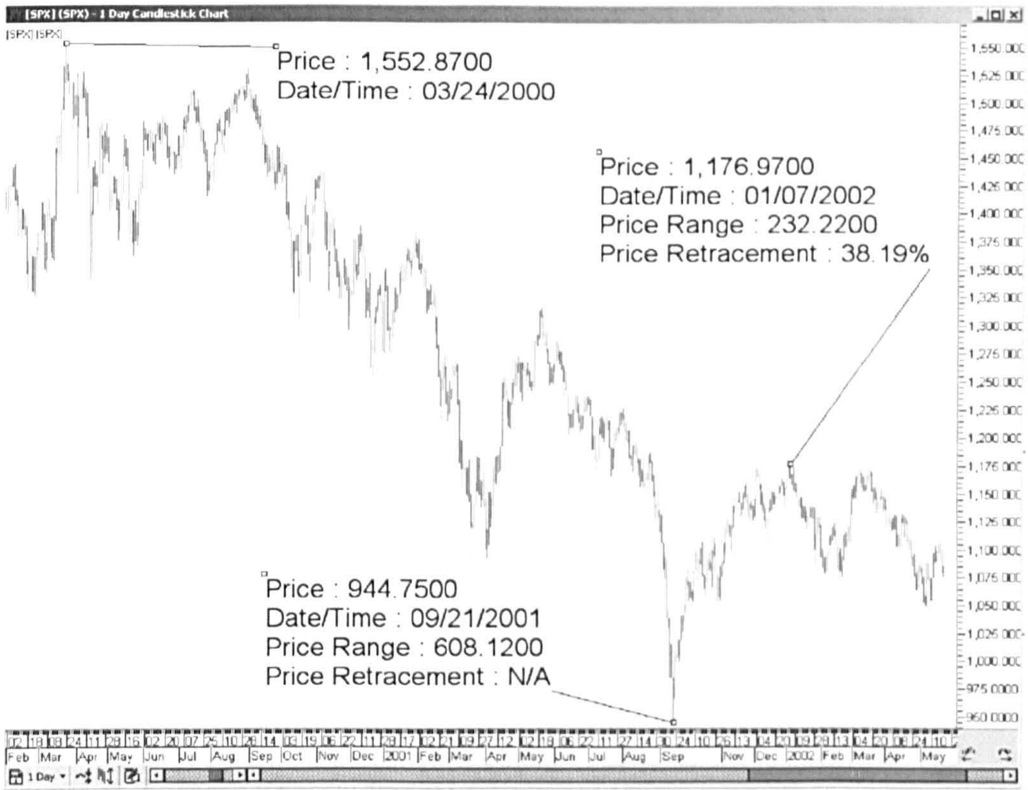
If such a phenomenon exists this would mean that market participants anchor expected cyclical phase amplitudes and durations on the amplitudes and durations of previous phases. This is why we have called such a phenomenon *Proportional Phase Anchoring*. The ratio between phases is often claimed to be an integer multiple of a previous phase being compared to or a half of it: 50%, 100%, 150%, 200%, etc. Claims vary between texts as to how useful the precision of these ratios is – many only advocate them as a rule of thumb. There are, however, more esoteric proportions examined by many technical analysts, the most widely used ratios stemming from the Fibonacci series and Phi.

Figure 2-9 – S&P: Longer Term Price and Time Retracements



The following examples show how an analyst would make use of two commonly used ratios from the Fibonacci series: 0.618 and 0.382. Figure 2-9 shows the May to September 2001 fall on the Standard and Poors 500 index. Here there is an example of a 61.8% price retracement (shown by the price labels) as well as a 61.8% time retracement (shown by the vertical lines) of this fall that halted the subsequent advance in December 2001. Despite the above explanations being in reference to uptrend corrections, this example is of a correction of a downtrend. The same 61.8% price retracement level outlined in Figure 2-9 is equal to the 38.2% price retracement in Figure 2-10. Figure 2-10 shows the same index, but inclusive of the data going back to the March 2000 all time high – the 38.2% price retracement is of the March 2000 to September 2001 decline (shown by the price labels).

Figure 2-10 – S&P: Shorter Term Price Retracement



2.5. TECHNICAL INDICATORS

The majority of the literature has not focused on the phenomena examined by pure chartism. The focus has been on mechanical implementations of various technical indicators, as these are more readily usable and assessable. They do require parameterisation, but present fewer problems than replicating visual pattern recognition.

Figure 2-11 – Technical Indicators

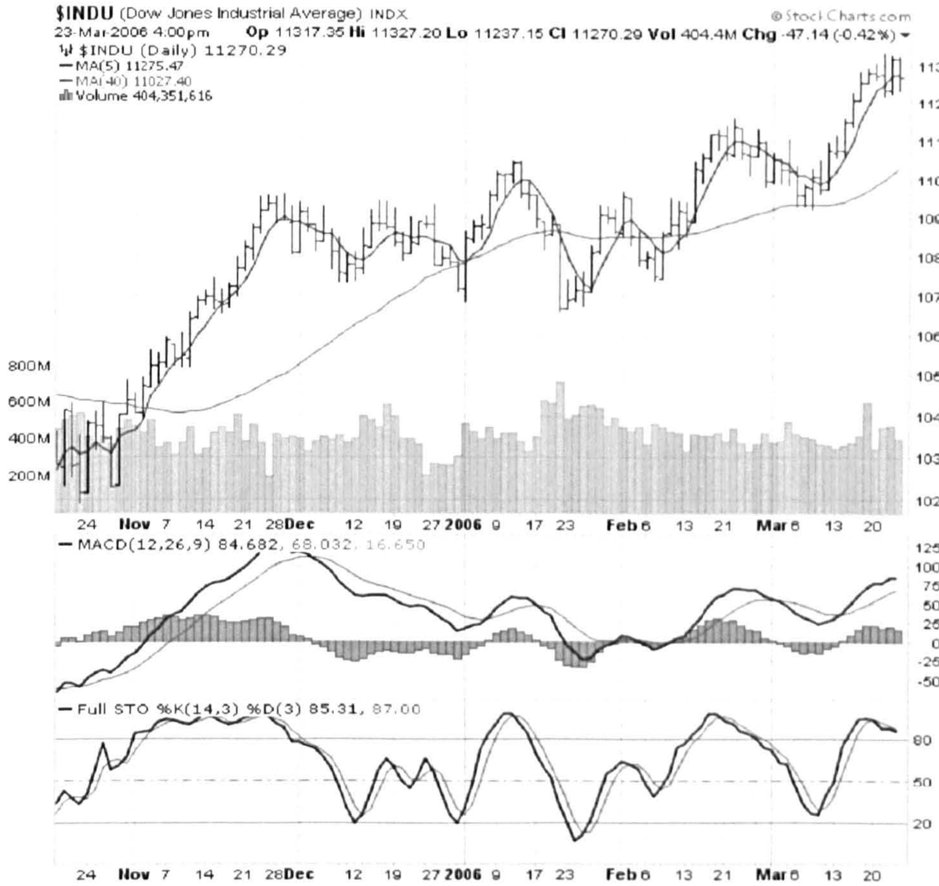


Figure 2-11 is stereotypical example of what a technical trader would look at. In the top pane one can see volume and historical prices with two simple moving averages of different sample sizes of closing prices. The trader would form pattern and trend analyses with these series. Below this one sees three other indicators that intend to capture cyclical oscillations in the market. There are a large number of indicators that seek to trigger trades by quantifying trends, oscillations and volatilities. "Filter rules" trigger trades in the direction of price moves greater than a defined percentage. They do not seem to appear in textbook technical analysis yet form the starting point for much of the literature in the area. Alexander (1961), Fama and Blume (1966) and Sweeney (1988) found no value in such rules in the equity markets. Sweeney (1986) and Levich and Thomas (1993) implemented a number of different sized filters on daily closing prices of major currencies in the years 1975-80 and 1976-1990 respectively. Large filters, up to 10% were profitable, with small filters of between 0.5% and 1% being significantly more profitable than would be expected by chance (Sweeney, 1986). Moreover, out-of-sample performance was also consistent. There was also a significant difference between the conditional returns and those from bootstrapped series (Levich and Thomas, 1993).

Moving averages are popular in practise and as topics of research but they have born contradictory results. When examined by Brock et al (1992) and Gunasekarage and Power (2001), excess profits were obtained. Yet as aforementioned, Sullivan *et al* (1999) criticised data-snooping biases in the work of Brock *et al.* Neural network systems driven by moving averages have found profitable application (Gencay 1996 and 1998) yet the moving average application in the forex markets have not found profitability (Lee and Mathur, 1994, Lee, Gleason and Mathur, 2001, Lee, Pau and Liu, 2001 and Olson, 2003).

It is an entire literature in itself, yet the field of applied machine learning is also relevant (Vapnik, 1998). Allen and Karjalainen (1998) used genetic algorithms to generate that a trading system that switched between stocks and T-bills between 1928 and 1995. Consistent excess out-of-sample returns were not achieved. Neely, Weller and Ditmar (1997) also used a genetic programming approach to identify trading rules across a variety of currencies in the period between 1975 and 1980 and then scrutinize their out-of-sample performance between 1981 and 1995. They also did not find consistent excess out-of-sample returns. It is important to note that the profitability of singular trading rules is consistently lower than the profits from the more complex genetic combination of a number of indicators (Neely and Weller, 1999).

2.6. FINANCIAL THEORY AND TECHNICAL ANALYSIS

Jegadeesh (2000) was disappointed that Lo *et al* (2000)'s title "Foundation of Technical Analysis" did not lead to a theoretical justification or potential coexistence with mainstream financial theory. Kavajecz and Odders-White (2004) claim that technical analysis can co-exist with the efficient markets hypothesis if it is understood solely in the context of liquidity provision, rather than forecasting a relationship with future prices. Transaction costs could be minimised through strategic limit order placement at previous extremes, where they found limit order book depth to be high. Whilst these empirical results are of value, the attempt to reconcile technical analysis and market efficiency appears strained. A deeper investigation of technical analytical rationale reveals interesting coincidences that may contain the building blocks to build that bridge.

Interestingly, many facets of modern traded markets seen as barriers to technical analysis are in fact the very environment that technical analysts are encouraged to trade in. The efficient markets hypothesis states that symmetrical information distribution and a high volume of trading means that opportunities are traded away and price alone is a useless predictor – yet textbook technical analysis actually identifies these as the fertile trading arenas. This prescription is clearly a paradox. Texts encourage technical analysts to focus on liquid markets where patterns and trends are believed to be "smoother" and a more persistent reflection of the market's perception of fundamental information (Hamilton, 1922, Gann, 1949, Pring, 1998, Achelis, 2000, Murphy, 2000 and Edwards and Magee, 2001). The technicians' belief in the central relationship between liquidity and information absorption runs to the very core of western technical analysis.

At the end of the 1800s, Dow stated the central tenet of his theory that "the market discounts everything" (Hamilton, 1922, Rhea, 1932, Brown, Goetzmann and Kumar, 1998 and Murphy, 2000). This is strikingly similar to EMH. Thus, according to *both* EMH and Dow Theory, the market has determined the "correct" price, discounting the past, present and known future. It is at this point that technical analysis texts claim that Dow Theory is thus the same as EMH and simplistically dismiss the challenge from modern financial theory. Murphy (2000) was rightly censured by Neely (1997) for this inadequate argument. This inadequacy is rooted in their differing assumptions and paradigms. When dismissing Murphy (2000)'s statement, Neely (1997) rightly took Murphy's statement for what it said, pointing out that Dow Theory's proposition that price contains the market's collective knowledge is not the efficient markets hypothesis. Technical analysis texts do not rigorously outline exactly how their understanding strays from generic EMH, even if it is mistaken. Technical analysts perceive the trend of prices at a particular time horizon as an additional piece of information in itself. Even when strong-form efficiency exists in an EMH paradigm, markets make continuous trends – prices generally do not "gap" without trading taking place between these levels. A technician would also suggest that the time-series of many types of fundamental data also contain persistent trends that drive market trends and make them persistent. If they made use of academic terminology perhaps they would call such trends "efficient trends." They would argue that such trends may last minutes or perhaps years and, if it exists, the concept would differ from the behavioural notion of rational trend chasing (Orosel, 1998).

It is clear that technical analysts have not adequately expressed what they believe and others have reasonably dismissed these half-explained claims, yet have not inquired further. Malkiel (1996) and Paulos (1995) point out that random walks also exhibit trends, suggesting that trends in financial time-series also start and terminate randomly. This assertion does become less tenable as one's time horizon increases. Presumably they are not suggesting that any macro-economic trends driving long-term equity trends are in fact a purely random occurrence. Neely (1997) points out that technical analysts do not claim their methods to be magical. They claim to take advantage of order-flow and the perception of fundamental news flow via trends in the markets. This idea of trend is what distinguishes Dow Theory from EMH and perhaps offers a contentious bridge to behavioural finance. Shiller (2002)'s demonstration of excess volatility in US equities versus fair value could be explained by private information fuelling investor overconfidence (Daniel, Hirshleifer and Subrahmanyam, 1998) or an initial under-reaction and later overreaction (Hong and Stein, 1999). If the former is true, such a marketwide effect would be an abject failure in the role of the Securities and Exchange Commission. If the latter is true, this is very similar to the guidelines offered by Dow Theory discussed previously. Dow suggested that long-term trends have three behavioural stages (Hamilton, 1922). Bull markets start with unnoticed accumulation by informed investors, continue as improved clarity in the fundamentals accelerates broad participation and end with speculative excess, overvaluation and overconfidence. Similarly, Dow suggested bear markets start with unnoticed distribution of positions by informed investors, continue as improved clarity in the fundamentals accelerates a broad sell-off and end with despair and undervaluation. Dow also saw an overlap between the first stage of a trend and last stage of the preceding trend. The framework is a cycle of under and overreactions that fuel later reversion to the mean and fundamental value. Dow's paradigm of behavioural waves remains core technical theory. It also forms the bedrock of much mainstream modern practice (see Soros, 1994). Whilst fragile, there is certainly a more than casual link between overreaction in behavioural waves versus the momentum phenomenon (Jegadeesh and Titman, 1993) and between the corrective behavioural waves versus the long-term reversal phenomenon (De Bondt and Thaler, 1985).

2.7. TECHNICAL ANALYSIS RESEARCH – AN APPRAISAL

Analysts, private traders, professional traders, hedge fund managers and mutual fund managers are all amongst those who use technical analysis. This diverse group will evidently use such tools in different ways. Forecasting may be the priority for the analyst versus trade profitability – two distinct objectives (Batchelor and Kwan, 1997 and Batchelor and Kwan, 2003). Different analysts may focus on different technical tools, as would different fundamental analysts, or a trader might use technical rules as triggers when exploiting mispricings. One may take an entirely systematic approach, an entirely discretionary approach or a combination of both. Furthermore these are all placed within the context of a trader's analysis of market conditions. The reality of this complexity is one that is far from matched by the simplicity of existing academic research and the poor explanations from technicians. Kavajecz and Odders-White (2004) point out the methodological difficulties created by the "art versus science quandary". Technical analysis and trading are often referred to by practitioners as arts to avoid scientific scrutiny, but accepting this subjectivity is as intellectually honest as it is uncomfortable. When examining the head and shoulder pattern, Dempster and Jones (1998[b]) found the pattern to be loss-making but avoided making conclusions for the whole body of knowledge of technical analysis. They restricted their conclusion to the unprofitability of trading every systematic formulation of this pattern in their sample and consider that *"many traders use implicit or explicit filters that aid their selection of 'winning' patterns. Furthermore, profitability can be gained from a well-informed or skilful exit policy that may well rely on exogenous information. (p. 21)"*. It must be stressed that this cannot mean that charting must be worthwhile. A burden of proof remains on technical analysts and those who claim to research that which analysts use.

Jegadeesh (2000) highlights that analysts do not use single tools in their analyses and "the usefulness of such conditional trading strategies is hard to verify objectively (short of directly evaluating a chartist's actual trades)". Batchelor and Kwan (2003) provide that evaluation and cast a shadow of doubt over the value of many existing empirical studies. They demonstrate the stark failure of even ex post optimised rules from the literature to yield significant profits compared to analysts' trade recommendations. Additionally, this was after adjusting for market frictions and, critically, none of the mechanical rules encapsulated the vital qualities of the analysts' recommended trading positions. They conclude that contemporary academic interpretations of technical analysis may "systematically understate" any potential value by assuming that traders follow simple mechanical trading rules. Of course it was not concluded that a speculatively efficient market would allow all analysts to be as successful.

We must then ask where the weaknesses may lie in the literature. 63% of technicians in a sample of leading technical analysts rated various chart-reading tools as their primary analytical tools (Batchelor and Kwan, 2001). Yet the academic literature focuses almost entirely on statistical indicators as these can be easily examined systematically. Dempster and Jones (1998[a] and 1998[b]) also point out that technical analysts do not rely on analysis of an individual security alone when making decisions. Analysts also examine other relevant series in an attempt to understand the market as a whole (Murphy, 1991 and 2000 and Ramyar, 2004). Such "intermarket analysis" may be as simple as analysing the price action or relative strength ratios of commodities related to particular equities or between securities, sectors or wider indices. Analysts also try to understand the extent of and the nature of the liquidity in the market. The Commitment of Traders reports, published by the CFTC, categorise open interest on US futures contacts and their options. Market Breadth indicators may also be used by equity analysts, advancing versus declining issues/volume or those others developed by technical analysts, the best known of which is the ARMS index (Arms, 1988 and Keswani, 2003). The role of active position management of (Lyons, 1998 and Bensaid and De Bandt, 1998) and position sizing in the light of stop order placement (Jones, 1999 and Vince, 1995) is well documented. Yet neither has received sufficient attention in the literature and the interplay between risk-control and a trader's emotional tolerances (Brady and Ramyar, 2004) is an avenue yet to be explored thoroughly.

To summarise, the evidence supporting the various technical analysis approaches is indeed mixed. The market microstructural evidence and analysts' forecasts of support and resistance levels appears sound. Yet implementing levels within simple trading systems yields mixed results. Moreover, the evidence for predictive power from chart patterns or employing statistical indicators in trading systems is just as contradictory. Nevertheless, neither central bank intervention, random walk, AR(1), GARCH-M nor

Exponential GARCH models explained the phenomena witnessed by the academic literature, even where these were also economically significant. Moreover, incremental information can exist even when accounting for these phenomena. Despite these interesting points, there remains a large gulf between the literature and industry practice and few examples of dialogue. Even optimising stylised academic technical tools in-sample can fail to replicate practitioner performance or the characteristics of their trades. Practitioners use a wide range approaches in a manner more complex than the literature generally assumes. Ironically this problem is not always eased by reference to industry textbooks.

3. MAGIC NUMBERS IN THE DOW

3.1. INTRODUCTION

This Chapter tests a popular but previously untested proposition about the behaviour of the stock market that was introduced in Chapter 2, the hypothesis of *proportional phase anchoring.* The proposition is that when the market changes direction after a period of trending prices, the magnitude and duration of the next trend is not random, but depends on the magnitude and duration of the previous trend. Specifically the thesis is interested in whether the ratios of successive trends cluster around Fibonacci ratios or "round numbers".

The idea that price trends may be arrested at predictable support and resistance levels is one of many tools used by technical analysts. Technical analysis – the prediction of turning points in financial markets by chart-based methods - has long been popular among practitioners, but viewed with suspicion by academics. Burton Malkiel, in his classic book writes, among many similarly cutting remarks - "Technical strategies are usually amusing, often comforting, but of no real value" (Malkiel, 1996, p161).

The root of the problem is the failure of technical analysts to specify their trading rules and report trading results in a scientifically acceptable way. Too often, rules are so vague or complex as to make replication impossible. Too often popular texts contain dramatic examples of successful predictions of turning points, with no count of misses or false alarms. Recently, however, academics have begun to look systematically at some of the more easily replicable technical trading rules. Park and Irwin (2004) provide a comprehensive review of these studies. Of 92 studies published in the period 1988-2004, 58 reported positive excess profits from a technical rule, 10 yielded mixed results, and 24 reported losses. Even allowing for a bias towards publishing positive results, and the possibility that not all studies properly accounted for transactions costs and risk, this does suggest that not all of technical analysis can be dismissed prima facie.

The Chapter falls into four sections. Section 3.2 below introduces our hypothesis and reviews relevant research findings. Section 3.3 introduces our data – high/low/open close prices for the Dow Jones Industrial Average in the years 1914-2002 - and develops a method for identifying turning points in range data based on Pagan and Soussonov (2003). Section 3.4 reports the resulting distributions of price and time ratios for successive trends, and compares them to distributions that would be expected to occur by chance using the Politis and Romano (1994) stationary block bootstrap methodology, again modified for the special features of our data.

3.2. SUPPORT, RESISTANCE AND FIBONACCI NUMBERS

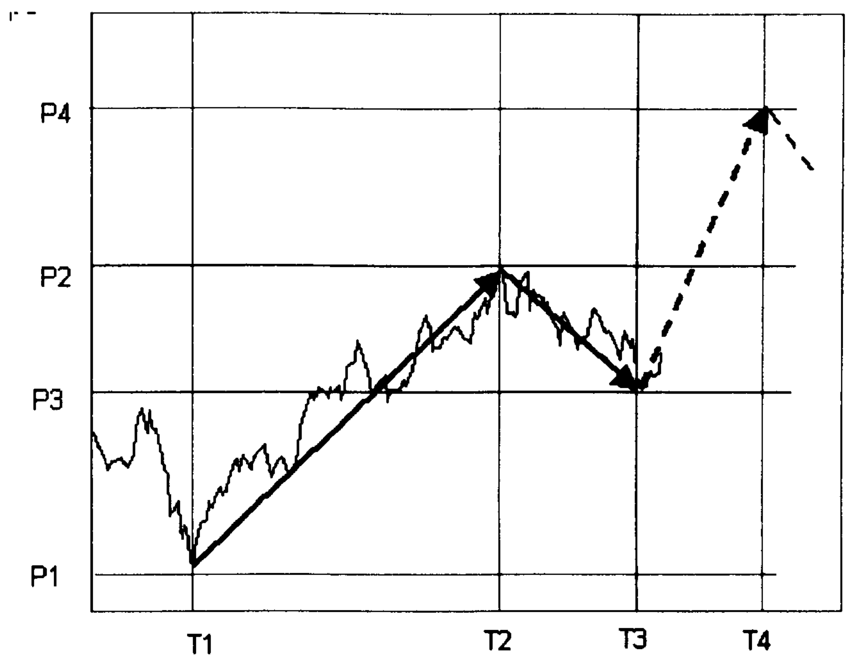
The popularity of technical analysis among market practitioners is evident from any casual reading of the financial press and the many web-based financial information services, and has been widely documented. Allen and Taylor (1992) and Lui and Mole (1998) find that technical analysis is used as a primary or secondary method of forecasting market trends by ninety per cent of players in the foreign exchange market. A third of currency traders rely on technical techniques exclusively (Cheung and Chinn, 1999; Cheung and Wong, 1999).

Technical analysis itself is an umbrella term for a heterogeneous set of techniques, some relying on visual recognition of chart patterns, others on values of statistical indicators calculated from recent price or volume data. Many practitioner books describe these techniques, most prominently Achelis (2000), Murphy (2000), Edwards and Magee (2001), and Pring (1998). Neely (1997) provides a readable academic summary. Academic research has focussed on the profitability of trading on mechanical technical indicators. Many early studies investigate filter rules that require a trader to go long if price rises more than k% above the most recent low price, and vice versa. Examples are the classic stock market studies of stock market efficiency by Alexander (1961) and Fama and Blume (1966), and the contrary finding of profitable filter rules in currency markets by Sweeney (1986) and Levich and Thomas (1993). More recent studies investigate moving average rules that require the trader to go long or short if the current price (or short term moving average of price) is above or below a long term moving average. LeBaron (1996) finds evidence that this generates profits in currency markets. Brock *et al* (1992) claim to find profits from applying moving average rules to the Dow Jones Industrial Average, though this is disputed by Sullivan, Timmerman and White (1999). A smaller number of studies evaluate pattern-based trades. Some look at trendline breaking rules that require the trader to buy or sell if the price breaks above some overhead resistance level, or falls through some lower support level (see for example Curcio *et al,* 1997). Others look at reversal pattern trades that require the trader to sell if some sequence of prices characteristic of the end of an upward trend appeared – the well-known "head-and-shoulders" or "double top" patterns for example. Lo, Mamaysky and Wang (2000) use local smoothing process to identify ten patterns often cited in technical analysis texts in a large sample of US stocks. They show that the statistical characteristics of returns change following familiar chart patterns, but stop short of claiming that this leads to profitable trading rules. Zhou and Dong (2004) use fuzzy logic to identify these patterns, but find no excess profits from trading. The study of the head and shoulders pattern in currencies by Chang and Osler (1999) does find some excess profits, but for only two of the six currencies examined, and in both these cases profits from the pattern based rules are lower than those from mechanical moving average rules.

The balance of this academic research does not mirror the relative way technical analysis techniques are viewed by practitioners in practice. From a small survey, Batchelor and Kwan (2001) find that the pattern–based methods, including use of support and resistance trendlines, are used much more often than moving average rules and other indicators, in both stock markets and currency markets. The attraction of technical indicators for academic research seems to be that the rules are easily formalised, while identification of chart patterns and support and resistance levels is a more subjective business. Also, much early academic research was aimed at testing market efficiency rather than understanding or evaluating technical analysts, when the realism of the trading rule is not an issue.

To put our own study in context, and to define some terms, consider the path of prices shown on Figure 3-1. The price has hit a *trough* at time T1 and price P1. It has then risen in a *bull phase* until it reaches a *peak* at time T2 and price P2. P2 can be regarded as a *resistance level.* The price then experiences a *reversal* and moves into a *bear phase* until another trough is reached at time T3 and price P3. P3 can be regarded as a *support level* for the price, which is then starting to turn up into another bull phase. The fall from (T2, P2) to (T3, P3) is termed a *retracement* of the bull phase (T1, P1) to (T2, P2). Any subsequent reversal into a bull phase, such as a rise from (T3, P3) to (T4, P4) is termed a *projection* of the previous bull phase (T1, P1) to (T2, P2).

Figure 3-1 – Bull and bear phases, retracement and projection



This kind of chart can form the basis for a trading rule so long as well-defined support and resistance levels exist, and can be predicted ex ante. The trading rule would require selling as the price approached the resistance level from below but failed to break it, and buying as the price fell near to the support level. If sufficient traders agreed on where resistance and support lay, and followed this strategy, their beliefs would become self-fulfilling, and price trends would be arrested at the resistance and support levels.

In a benchmark study, Osler (2000) asked currency analysts at six major US banks to supply daily support and resistance levels for three major currencies from January 1996 to March 1998. There are three interesting features of her data. First, quoted support and resistance levels are very often "round numbers". Second, for any individual firm the levels did not change dramatically from day to day, so there is some consistency in choices about support and resistance levels. Third, there was only limited agreement among analysts about where these critical price levels lay, suggesting that a variety of rules were used to determine these levels. In spite of this heterogeneity, Osler (2000) finds that exchange rates "bounce" off the levels quoted by the analysts much more often than from randomly chosen levels. This strongly suggests that reversal trades are indeed triggered when prices approach support and resistance levels and that there is some rationale for analysts choosing these levels.

The phenomenon of price clustering around round numbers – that is, price levels ending in 0 or 5, or 00 and 50 - has been confirmed in the currency markets (de Grauwe and Decupere, 1992) and in stock indices (Donaldson and Kim, 1993; Ley and Varian, 1994; Cyree and Domian, 1999; Mitchell, 2001). These are often called "psychological barriers", but Osler (2001) shows that there are good market-driven reasons expecting support and resistance at round numbers. Many currency trades are made in response to conditional retail orders (for example, stop-loss and limit orders) and these are very often set at round number exchange rates. Option strike prices are almost invariably round number values of the underlying currency or index, and cash prices around the strike price are liable to induce exercise or hedging trades in the cash market.

Imagine then that we have just passed time T3 on Figure 3-1, and the price has started to rise above P3. How can the likely target resistance level P4 be forecast? In addition to looking for round numbers above P3, technical analysts have two systematic ways of determining support and resistance levels. One is to identify them as previous peaks and troughs, the minima or maxima achieved over some window of past price data. The longer the window, the wider the band between support and resistance, and analysts typically quote a number of possible support and resistance levels, corresponding to different window sizes. The rationale for this approach is that the recent maxima and minima reflect price levels at which sellers and buyers have caused reversals in price in the past. Unless there has been some fundamental change in sentiment one might therefore expect them to enter the market again at these levels in the future. As a variant on this method, analysts may draw "trendlines" through recent minima and maxima, and base their support and resistance levels on an extrapolation of this channel. Again, the longer the window of past data used, the wider the band between support and resistance. The rationale here is that the trend accounts for likely changes in fundamental sentiment.

The second way that analysts determine the target price P4 – and the focus of this Chapter – is by means of what we term "magic numbers". Many analysts believe that the ratio of the size of the prospective rise in price $|P4\text{-}P3|$ to the size of the preceding fall $|P3\text{-}P2|$ is not random, but is likely to lie close to one of a small number of critical ratios. As outlined in the discussion of proportional phase anchoring in Chapter 2, these retracement ratios themselves may be either "whole numbers" like 0.5, 1, 1.5 etc., or may be one of the set of Fibonacci ratios 0.382, 0.618, 1.618, etc. Similarly, many analysts believe that the ratio of the prospective rise in price $|P4\text{-}P3|$ to the previous bull phase price rise $|P2\text{-}P1|$ is likely to be close to one of these key ratios. Some analysts argue that ratios of *durations* of successive runs, say $|T4\text{-}T3|/|T3\text{-}T2|$ may also follow some Fibonacci rule.

A Fibonacci series is an ordered set of numbers f_1, f_2, f_3, f_4, …, f_{i-1}, f_i, … where terms from f_3 onwards are the sum of the two preceding numbers in the series. The Fibonacci ratio is $\phi = \lim_{i\to\infty} (f_i/f_{i-1}) = 1.618034\ldots$ Related ratios are $\phi^2 = \lim_{i\to\infty}$

$(f_i/f_{i-2}) = 2.618034\ldots$, $\phi^3 = 4.236068$, and their inverses 0.618034 …, 0.381966.., and 0.236068. The number ϕ occurs naturally in the geometry of the pentagon, and in spiral forms found in botany and biology (Basin, 1963). All textbooks in technical analysis devote considerable space to description and discussion of these ratios. For example, Murphy (2000) asserts that 0.5 and 0.618 are the key ratios for determining target prices in retracements. Other ratios include 0.382, 0.786, 1, 1.5. 1.618,2 and 2.618. The proportions primarily used by technical analysts are given in Appendix 3-1. Figure 3-2 lists a few of the many citations of Fibonacci ratios in technical comments by respected market sources, including the Financial Times, Reuters, Dow Jones and Standard and Poors Money Market Services, covering bond, stock, forex and commodity markets during just three unexceptional days in 2004.

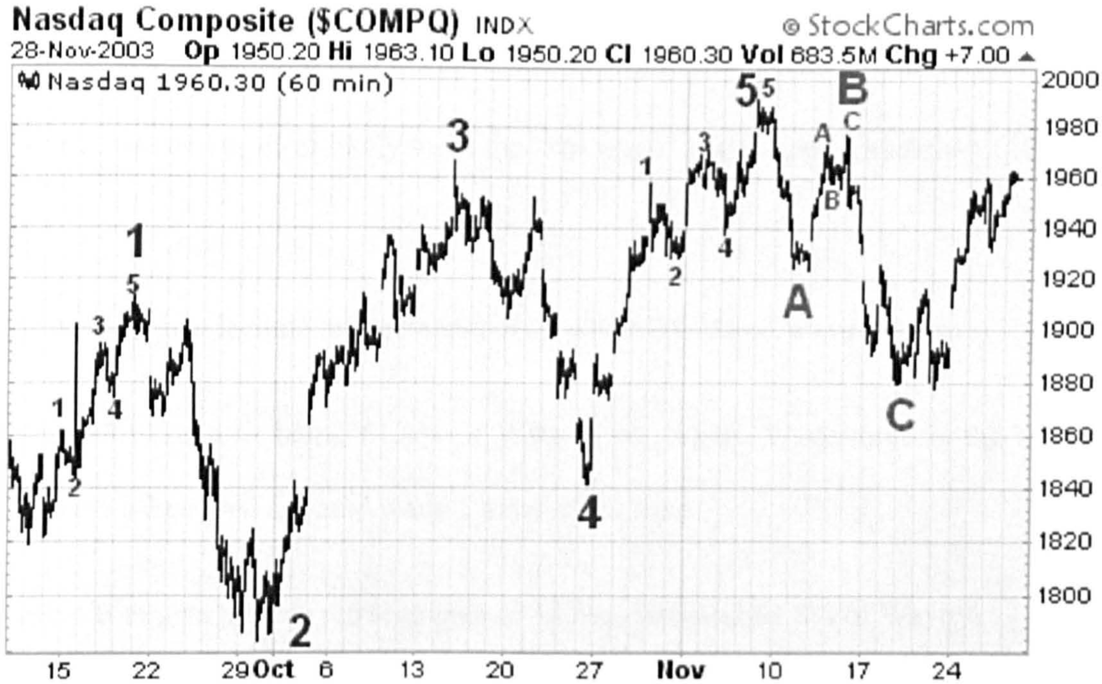
Figure 3-2 – Fibonacci ratios in the market, 6-8 October 2004

Crude tops charts but spike above $70 may flag top, *Reuters News* (8th October 2004)	"For upside targets on NYMEX crude Walter Zimmermann at United Energy looked at equality based projections, pegging the 1.618 percent Fibonacci projection at $69.45"
Charting Europe: Cable to Stage Recovery Vs Dollar, *Dow Jones Capital Markets Report* (8th October 2004)	"The 61.8% Fibonacci retracement at $1.8005 is also important and a possible price target"
MNI Eurozone Bond Technicals, *Market News International* (8th October 2004)	"RES 5: 116.56 61.8% of 111.00 to 120.00 SUP 3: 114.94 50.0% of 116.18 to 113.69 COMMENTARY: Bear-divergence on daily studies continues to favour a move towards the 115.34 congestion area. A break below there puts the 115.12 low back into focus and targets move to 114.94 Fibonacci level"
NYMEX crude softer, but holds above $52, *Reuters News* (8th October 2004)	"We have been looking at a Fibonacci (technical) extension of $52.91, which was just breached on Thursday, that could be a potential top," said a New York broker"
Nybot Dec Coffee Holds Support For Now, *Dow Jones Commodities Service* (7th October 2004)	"While Dec coffee futures have been in a minor downtrend off the Sept. 27 peak of 86.40, for now key Fibonacci retracement support has not been broken. Looking at the rally from the Aug. 16 low at 67.90 to the Sept. 27 peak, 61.8% of those gains comes in at roughly 75.00 even…Conversely, if a breakdown is seen and Fibonacci support at 75.00 falls, a fresh wave of long liquidation is likely"
Debt Futures Review: Slight Pullback While Awaiting Jobs Data, *Dow Jones Commodities Service* (7th October 2004)	"The 112-25 level represents a 61.8% Fibonacci retracement from the decline from the recent high to the session low, said Kosar. The 113 handle is roughly the low from Sept. 24"
Singapore Dlr Down Late On Weak Yen, High Oil; Bonds Flat, *Dow Jones International News* (6th October 2004)	"Technical analysis suggests the U.S. dollar's near-term bias against the Singapore dollar has improved after it clearly rose above Fibonacci resistance at S$1.6887, which is 50% retracement of the fall from Sept. 28, in Wednesday's Asian session"

While there is clear logic in the use of round numbers or recently realised extreme values as support and resistance levels, it is not at all clear why the ratio $|P4-P3|/|P3-P2|$ should be 0.618 rather than say 0.816. One possible argument is aesthetic. The length of a Fibonacci-determined bull run "looks right" on a chart relative to the previous bear phase – neither too short nor too long – and only at this point will sellers feel the market has risen too far. Enthusiasts for "the golden ratio" ϕ have claimed to see it in the proportions of classical architecture and art, and it was very consciously used by the 20th century architect Le Corbusier. However, many speculations about ϕ appear to be the result of visual "data mining" and wishful thinking – a judicious choice of where exactly to start measuring the base of the Parthenon, for example, or the selection of only those artworks that display prominent verticals about 61.8% from their left hand edge. The debate about the status of ϕ in art is summarised in the entertaining and informative monograph of Livio (2002). At a more fundamental level, the pioneering psychologist Gustav Fechner (1876) conducted experiments that seemed to show that people had preferences for rectangles with sides approximately in the ratio $1:\phi$. This idea was challenged by Godkewitsch (1974) but has since found some support (see for example McManus, 1980).

Another argument for using Fibonacci ratios in determining support and resistance levels is purely empirical, or possibly supernatural. Early in the history of stock market indexes developed by Charles Dow, editor of the Wall Street Journal from 1900-1902 and part-owner, commentators viewed their evolution as a series of nested irregular "waves". A central tenet of Dow Theory, as codified by Nelson (1903), Hamilton (1922), and Rhea (1932) is that the market has a cycle wave that lasts between 2 and 10 years, interrupted by shorter term primary (about 1 year), secondary and tertiary fluctuations. Dow theory also contains some statements about the likely shape of these waves. Hamilton, for example, asserts that "secondary movements retrace 33% to 66% of the primary move, with 50% being the typical amount". Cowles (1934) tests the value of Hamilton's stock tips, which to some extent follow from Dow Theory, but with negative results. Hamilton's reputation as a forecaster is rescued by the reappraisal in Brown, Goetzmann and Kumar (1998). Elliott (1938)'s extension of Dow theory takes some analysts into esoteria and a rather different wave theory of the stock market. His basic idea is that the market typically rises in five waves or phases (bull, bear, bull, bear, bull), and then falls in three phases (bear, bull, bear). Moreover, this pattern is self-similar and can be seen at all data frequencies, so that within each long term wave there are five rising and three falling phases, and within each of these are similar patterns: and so on. So Elliott Waves might be observed in the century long term stock market history, in a chart of last year's fluctuations, or in today's chart of 5-minute price bars. Figure 3-3 shows an Elliott Wave pattern superimposed on two months data on the NASDAQ index. The numbers 1, 2, 3, 4, 5 show the turning points in the up-trend, and the letters A, B, C show the turning points on the downtrend. Within the major waves one some minor waves are also shown.

Figure 3-3 – Some Elliott Waves in the NASDAQ



In a later newsletter Elliott (1940) further claimed that *specific* waves are key proportions of *specific* preceding waves or pairs of waves. So in Figure 3-3, one might expect the retracement ratio of the price range between turning points 2 and 3 to be a Fibonacci ratio multiple of the range between points 1 and 2. Or one might expect the projection ratio of the range from B to C to be a Fibonacci ratio multiple of the range between points 5 and A. Prechter and Frost (2000, 10th ed.) outline the basic, stylised ideal proportionality between identified waves (Table 3-1).

Table 3-1 – The Base Elliott Wave Proportionality Framework

Wave 2 targets include retracements of 38.2%, 50% and 61.8% of Wave 1
Wave 3 is seen as most likely to be the "strongest" wave, approximately 1.618 times Wave 1
Wave 4 targets include retracements of 23.6% or 38.2% of Wave 3
Wave 5 is seen as being 61.8% of Wave three, where Wave three is the longest wave. Wave 5 is believed to equal wave 1 most of the time
Wave B targets include retracements of 38.2%, 50% and 61.8% of Wave A
Wave C is seen as being equal to or 161.8% Wave A
A minimum corrective wave, correcting a five wave impulse wave, would comprise of a 38.2% time retracement and a 50% price retracement of that entire impulse wave

Elliott believed that this followed from some underlying mathematical principle driving a wide range of physical and sociological phenomena, and published his beliefs in a book entitled "Natures Law – the Secret of the Universe" (Elliott, 1946). The Elliott Wave was subsequently much elaborated and popularised from the 1970s onwards by Prechter and Frost (2000, 10th ed.), with considerable success. Fibonacci ratios are mentioned more often than moving averages in the Batchelor and Kwan (2001) survey of techniques used by practising analysts. There are other layers of both price and time proportionality that are offered by Prechter and Frost and Neely and

Hall (1990) in an Elliott Wave structure, both between waves and within sets of waves. This all depends on the extreme subjectivity of Elliott Wave counting that Mandelbrot (1999) dismissed outright. For this reason, any objective examination of proportional anchoring must be independent of any perceived Elliott structure in price trends.

Some adherents of wave theory use methods attributed by Gann (1942, 1949), though these are less popular than Elliott Wave analysis. In a long and apparently successful career as a stock tipster and seller of trading systems, Gann promulgated the idea that prices retraced to some predictable "round fraction" of the previous trend – usually 0.5, but possibly any multiple of 1/8. He applied these and other "market geometry" techniques to predict the timing as well as the level of likely turning points. There seems to be no logic for the ratios used by Gann, who found justifications for his many different trading systems in numerology, astrology and Biblical arcana.

The idea that prices retrace to a Fibonacci ratio or round fraction of the previous trend clearly lacks any scientific rationale. However, this phenomenon is well bedded into the mind of the marketplace, and so may be self-fulfilling. In the essays collected in Kahneman, Slovic and Tversky (1982), the authors note that in an uncertain environment people tend to "anchor" decisions to available numbers, regardless of relevance. In the classic Tversky and Kahneman (1974) experiment, a number is chosen at random by spinning a wheel of fortune, and subjects are asked to whether the percentage of African nations belonging to the United Nations is higher or lower than that number, and to estimate the exact percentage. There is a high correlation between the number from the wheel and the percentage estimate, even though the events are obviously unconnected and the choice of number random. The mechanism of anchoring is disturbingly close to the environment of the trader. In the language of Chapman and Johnson (2002), subjects (traders) are presented (by technical analysts) with a salient but uninformative number (a Fibonacci ratio) before making a judgment (price target). So it is simply human nature for traders to take the technical support and resistance levels as starting points for thinking about price targets, regardless of their logic.

Most people are also subject to the "illusion of control", and confronted with random events or time series will claim to see patterns rather than admit to the existence of coincidence or randomness. This is particularly acute in business environments where an appearance of competence must be maintained. Fenton O'Creevy, Nicholson, Soane and Willman (2003) report an experiment in which professional traders were asked to use a computer mouse to control a dot on the screen. In reality, the movements of the dot were random and the mouse was not even connected to the computer. But the traders happily reported that they were learning a rule linking the two, and controlling the dot.

Regardless of whether Fibonacci ratios are natural laws or optical illusions, the proposition that stock prices retrace to such levels is unusual among technical trading rules, in the sense that it can be clearly formulated in numeric terms, and is potentially testable. Provided, that is, that one can identify the peaks and troughs the price series.

3.3. IDENTIFYING PEAKS AND TROUGHS IN THE DOW

The data for our analysis are daily observations on the Dow Jones Industrial Average (DJIA) for 22,194 trading days between January 1915 and June 2003 (Appendix 3-2). From January 1914 to October 1928 we have only closing prices for the index.

Thereafter we use daily open, high, low and close prices. The index does not include dividends, since the research interest is in identifying cycles that might be observed by traders rather than computing returns to any trading rule.

Dating the peaks and troughs in nonstationary time series has long been of concern to business cycle analysts, and in recent years their methods have been applied also to identifying cycles in the stock market. The problem is to find some way of filtering out noise from the time series so that underlying bull and bear market trends can be revealed, and the peak and trough prices and dates accurately identified. A technical analyst would do this by eyeballing the chart, and marking trends with a ruler, or the line drawing tool on some software package. Objective research needs a more systematic method that ensures turnings points are identified in a consistent way throughout the time series, and that makes explicit the rules by which the turning points are chosen.

There are a number of ways to approach to the problem, depending on how much structure is imposed on the underlying time series.

The first is a simple filter rule. Suppose that we are in a bull market, and the highest price achieved so far occurred at time t. If subsequently the cumulative fall in price from the high is more than some threshold percentage (say 10%) then we can say that a peak occurred at t, and the price series has switched from a bull to a bear phase. A similar rule can be used to identify troughs. This approach is used in Chauvet and Potter (2000), and in Lunde and Timmerman (2003) who investigate symmetric and asymmetric filters in the range 10%-20%. Lunde and Timmerman elaborate and formalise the concept further (Table 3-2). Narrow filters generate many turning points, while broad filters discount short term reversals and generate a smaller number of turning points and hence longer bull and bear trends. Even this simple approach requires some subjective judgment about what constitutes a reasonable decomposition of the price series into trend and noise components. As it stands the rule is liable to generate larger numbers of turning points at times of high market volatility, so a variable filter size might give more plausible results. Levy (1971) used a more dynamic form of percentage switching. The highest (lowest) point preceding a decline (advance), with the filter $c = a + bV$, where a and b are constants, fixed by Levy as $a = 0$ and $b = 6$, and V is 131-day percentage volatility. Levy percentage filter was thus completely driven by volatility and made no use of constants.

Table 3-2 – Percentage Turning Point Filter (Lunde and Timmerman, 2003)

I_t is a market state dummy variable taking the value 1 (0) if the stock market is in a bull (bear) market at time t. Measuring time on a discrete scale, suppose that at t_0 the market is at a local maximum, meaning $P_{max} = P_{t0}$, where P_{t0} is price at t_0. The threshold filter that triggers a switch between bull and bear states is c and $\tau \geq 1$ is a stopping time variable defined by

$$\tau = \min_{i=1,\dots,n}\{P_{t_{0+i}} \geq P_{\max} \vee P_{t_{0+i}} < (1-c)P_{\max}\}$$

When the first condition is fulfilled the local maximum in the current bull state is updated

$$P_{\max} = P_{t_{0+\tau}}, t_{\max} = t_{0+\tau}$$

The continuation of the bull regime between t_0 and $t_{0+\tau}$ means that $I_{t0} = \dots = I_{t0+\tau} = 1$. Conversely, if $P_{t_{0+i}} < (1-c)P_{\max}$ is met, fulfilling the second condition, a bear market is defined as existing between t_0 and $t_{0+\tau}$ thus $I_{tmax} = \dots = I_{t0+\tau} = 0$. As per bull markets, the above holds for bear markets as:

$$P_{\min} = P_{t_{0+\tau}}, t_{\min} = t_{0+\tau}$$

$$\tau = \min_{i=1,\dots,n}\{P_{t_{\min+i}} \geq P_{\min} \vee P_{t_{\min+i}} < (1-c)P_{\min}\}$$

Secondly, a filter might take the form of a time filter. Swing charts (Gann, 1942, 1949) are practitioner rules that switch state based on duration based filter of price moves. An open/high/low/close series should move in a direction for at least x consecutive days to not be designated as mere noise and ignored. For a swing to turn up (down) a market must have a x bars where the high (low) of the bar is higher (lower) than the previous bar and the low (high) is higher (lower) than the previous bar, where 3 is the normal value of x. A choice needs to be made as to how to treat inside and outside bars, bars that are enveloped by or envelope the previous bar. They can be ignored or swing changes can be based on the close prices. Swing charts are perhaps analogous to Okun's now popular rule of thumb that two or more quarter's negative growth constitutes a recession (see Layton and Banarji, 2003) and more loosely to duration dependence. There is no academic literature on this switching approach but their role in industry, simplicity and their claimed robustness makes of them interesting for future research.

A third approach is to apply a more complicated heuristic that enforces some desirable features on the turning points and market phases. A good example is the procedure developed for stock market analysis by Pagan and Sossounov (2003). This is derived from the pioneering paper on the determination of business cycle peaks and troughs by Bry and Boschan (1971), which in turn automated the task performed by the NBER's Business Cycle Dating Committee (see Burns and Mitchell, 1946). The 3 step process outlined by Pagan and Sossounov (2003) is shown on Table 3-3. Edwards, Biscarri and de Gracia (2003)'s formalisation is included along with additional formal expression of the original three point table. The parameters used reflect the monthly frequency of the price data used in their study, and are explicitly selected to yield cycles consistent with Dow Theory. Provisional peaks and troughs are identified as the highest and lowest points in a moving k-month (8-month) window. Any cases where there are successive peaks or troughs are resolved and any odd effects that occur at the start or the end of the series, where the window width necessarily shrinks, are also removed. Finally, to address the problem of excessive numbers of cycles being generated at times of high volatility, any cycles or trends that look too short (cycles less than 16 months, phases less than 4 months) are removed, unless they correspond to an obvious market crash. Similar methods are used by Edwards *et al* (2003) and Gonzalez, Powell and Shi (2003).

Table 3-3 – Pagan-Sossounov (2003) procedure for identifying turning points

1. Determination of initial turning points in raw data.

Determination of initial turning points in raw data by choosing local peaks / troughs, as occurring when they are the highest /lowest, values in a window 8 months on either side of the date.

Enforcement of alternation of turns by selecting highest of multiple peaks (or lowest of multiple troughs

2. Censoring operations.

Elimination of turns within 6 months of beginning and end of series.

Elimination of peaks (or troughs), at both ends of series which are lower (or higher) than most recent.

Elimination of cycles whose duration is less than 16 months.

Elimination of phases whose duration is less than 4 months, unless fall/rise exceeds 20%, .

3. Statement of final turning points

As formally expressed in relation to monthly data by Edwards et al (2003), there is a peak at price p_t and time t if $[p_{t-8},...,p_{t-1} < p_t > p_{t+1},...,p_{t+8}]$ and there is a trough at price p_t and time t if $[p_{t-8},...,p_{t-1} > p_t < p_{t+1},...,p_{t+8}]$

We can alternatively express this as peaks occurring when $p_t >= \max(p_{t-8},...,p_{t-1}, p_{t+1},..., p_{t+8})$ and troughs when $p_t <= \min(p_{t-8},...,p_{t-1}, p_{t+1},..., p_{t+8})$.

We have formally expressed the written definition given by Pagan and Sossounov of phase filtering as follows, where D is duration, A is the amplitude (phase returns), T is the turning point being identified, t is the time of the turning point and F_t is a dummy variable, where $F_t = 1$ when $A_{phase} > \min(A_{phase})$ and $F_t = 0$ when $A_{phase} < \min(A_{phase})$

$[\min(phase) = \min(D_{phase})(1 - F_t) + \min(A_{phase})F_t]$

Where $D_{phase} = t_T - t_{T-1}$; ($\min(D_{phase})$=4 months) and $A_{phase} = abs\left(\frac{p_T - p_{T-1}}{p_{T-1}}\right)$;

($\min(A_{phase})$ =20%)

A sixteen-month minimum peak (trough) to peak (trough) cycle rule is imposed, rather than the original Bry Boschan fifteen months. We can formally express the definition given by Pagan and Sossounov as follows

$\min(D_{peakcycle}) = 16$ months	$\min(D_{troughcycle}) = 16$ months
where $D_{peakcycle} = t_P - t_{P-2}$	where $D_{troughcycle} = t_T - t_{T-2}$

The choice of an eight month rolling window is more restrictive than the original Bry and Boschan choice of six months. Pagan and Sossounov (2003) accept the lack of clarity as to how one selects an appropriate value in the context of asset prices. For example, Gonzalez *et al* (2003) identify all peaks (troughs) that are higher (lower) than all points *five months* on either side – the highest (lowest) of multiple peaks(troughs) are then selected. Whilst no justification is given by Pagan and Sossounov for eight months in particular to be used either side of the window, there is one given for the alteration of the minimum time to be spent in each phase. Pagan and Sossounov (2003) describe Dow Theory as amongst the "oldest formal literature emphasising bull and bear markets". As their work "shares an interest with Dow theorists a fundamental interest in primary movements", Dow's guidelines steered the remaining parameterisation of the model. Dow's suggestion of minimum phase durations of three months formed the basis of final choice of four months. Yet the impact of fat-tails would mean that this filter would ignore some of the important, yet short-lived, swings in price. The 1987 crash only lasted three months for example. They felt that reducing the four months to three would catch too many spurious cycles and so the minimum phase requirement was amended. Where there is a swing of at least twenty per cent, the four month filter is overridden. Gonzalez *et al* (2003) were also uncomfortable with the blanket requirement that each equity market phase have a duration of at least five months. They instead replaced it with a restriction entirely based on minimum returns – a minimum 10% phase rule. Whilst in the context of GDP based business cycle identification, Artis, Kontolemis and Osborn (1995) also altered the amplitude requirement of the BB approach, imposing a minimum amplitude of one standard error of the monthly growth rate. These are all of course also blanket requirements, just ones that differ from the original 1971 assumptions.

The strength of the Pagan and Sossounov approach in censoring phases lies in it having a phase filter conditional on either phase amplitude *or* duration.

Pagan and Sossounov (2003) refers to Dow's definition of a primary bull market as being one that lasts, on average, for at least two years (yet can be interrupted by secondary corrections). It was felt that a two-year restriction would disallow the identification of primary corrections, which would likely be shorter in duration than their bull counterparts in equity markets. With Dow Theory suggesting that a complete cycle lasts one year at the minimum and the original Bry Boschan approach giving fifteen months, sixteen months was settled on. This results in a neat 16, 8, 4 parameterisation of the duration parameters for long term equity cycles.

Lo, Mamaysky and Wang (2000) use a fourth, and apparently more objective, method to identify peaks, troughs and local reversal patterns in high frequency data on US stocks. Turning points are identified as points with zero time derivatives in kernel regression functions fitted to moving windows of closing price data. Although this looks less arbitrary than the heuristic approach, in practice many ad hoc adjustments and subjective judgments have to be made. Successive peaks and troughs, and points of inflexion have to be removed. As with the Pagan-Sossounov procedure, the window size has to be determined, depending on the desired number of cycles. Interestingly, the window sizes automatically chosen by their regression package on the basis of an estimate of the noise-signal ratio (large) produced too few turning points in the opinion of an expert technical analyst who audited the Lo, Mamaysky and Wang (2000) procedure. The authors therefore narrowed the window size to bring the results closer to market practice.

The fifth possibility is to identify turning points by some Markov switching model of the type popularised in business cycle analysis by Hamilton (1989), and compared to the heuristic approach by Harding and Pagan (2003a). The idea is to characterise stock returns as coming from either a bull state (positive mean, low variance) or a bear state (negative mean, high variance), with some high probability of staying in each state once the bull or bear market is under way. The means, variances and probabilities can be estimated from time series data on prices, and from these one can infer the probability that the market was in a bull or bear state at each point in the time series. Dates at which the probability of being in the bull state fall from above 0.5 to below 0.5 count as provisional peaks, and dates when this probability cuts 0.5 from below count as provisional troughs. Bodman and Crosby (2002) argue that these regime switching models are "non-judgmental", and in his comment on Harding and Pagan (2003a) Hamilton (2003) similarly agues that they capture the underlying structure of the time series. However, as Harding and Pagan (2003b) point out, the objectivity is more apparent than real. Choices have to be made about the number of states, the time series process driving the means and variances, whether the transition probabilities are time varying and if so whether they are dependent on the duration of the regime. Guidolin and Timmerman (2002), for example, successfully parameterise 3-regime models of returns to UK bond and stock markets. Rather importantly, the results of these switching models may well violate common sense, in that the switch points need not occur at local peaks or troughs. Harding and Pagan (2003b) also argue that Markov cycle models are not intuitively transparent. There is a lack of any intuitive meaning in the estimated parameters over and above the knowledge that they represent the probability of being in a state.

We have chosen to identify turning points in the Dow using the approach of Pagan and Sossounov (2004), with two modifications that we have developed for this Chapter. One is that the methodology employs daily high and low price series as potential highs and lows respectively, rather than the closing price. This recognises that technical analysts in practice employ charts with daily bars rather than single points. It does make a difference to cycle dating. For example, a trough in the Dow identified at a level of 416.2 in October 1957 (the lowest low) would not have been identified by the Pagan-Sossounov algorithm, instead being put at 424.2 (the lowest close) in December 1957. A second is the addition of the censoring rule that any peaks (troughs) are greater (less) than their preceding trough (peak), to ensure appropriate alternation. This is in addition to the alternation censor specified by Pagan and Sossounov (2003), which simply ensures that peaks (troughs) are followed by troughs (peaks).

As noted by Biscarri and de Gracia (2001) and Edwards *et al.* (2003), the Pagan-Sossounov procedure is quite sensitive to the window size used for initial identification of turning points. One could parameterise the Pagan and Sossounov model in such a way to segment a long time series into a handful of extremely large phases or several hundred small phases. As an illustration, our model with Pagan and Sossounov's parameters (a 16-month window with a minimum cycle length of 16 months) identifies 46 turning points in the Dow between 1915 and 2003. Halving the window size increases the number of turning points to 60. Combining this smaller window size with a minimum cycle of 8 months, rather than 16, increases the number of turning points further to 72.

Table 3-4 – Comparison post-war turning points with Pagan-Sossounov (2003)

Peaks

Batchelor-Ramyar	Pagan-Sossounov
29 May 1946	May-46
14 June 1948	Jun-48
05 January 1953	Dec-52
09 April 1956	Jul-56
04 January 1960	Jul-59
15 November 1961	Dec-61
09 February 1966	Jan-66
02 December 1968	Nov-68
28 April 1971	Apr-71
11 January 1973	Dec-72
22 September 1976	Dec-76
11 September 1978	
27 April 1981	Nov-80
30 November 1983	Jun-83
25 August 1987	Aug-87
	May-90
03 June 1992	
	Jan-94
14 January 2000	

Troughs

Batchelor-Ramyar	Pagan-Sossounov
30 October 1946	Feb-48
14 June 1949	Jun-48
15 September 1953	Aug-53
22 October 1957	Dec-57
25 October 1960	Oct-60
25 June 1962	Jun-62
10 October 1966	Sep-66
26 May 1970	Jun-70
23 November 1971	Nov-71
09 December 1974	Sep-74
01 March 1978	Feb-78
27 March 1980	
09 August 1982	Jul-82
25 July 1984	May-84
20 October 1987	Nov-87
	Oct-90
05 October 1992	
	Jun-94
21 September 2001	

Table shows dates of peaks and troughs from applying the Batchelor-Ramyar heuristic filter to daily data in the year 1945-2001, compared to the chronology of Pagan and Sossounov (2003). Shaded area show times when there are more than three months difference between turning points in the

The algorithm is also sensitive to data frequency. Pagan and Sossounov (2003) used monthly S&P returns, while the Batchelor-Ramyar procedure is applied using daily data. Adjusting their censoring parameters for daily data using a 252 day trading year, the procedure finds 46 cycles from monthly data, 52 from weekly and 47 from daily. Table 3-4 compares the dating of the post WWII cycles from their monthly data with the dates found using our method for daily data. There is general agreement about timing until the 1980s. Of the 16 cycles identified by Pagan and Sossounov, our dates for troughs are within three months of theirs in 12 cases, and in the case of peaks our procedure agrees in 11 cases. The concordance breaks down completely at the end of the sample, and we have one additional cycle in 1978-80.

The cycles found by Pagan and Sossounov are of roughly the same periodicity as the underlying economic business cycle. This is not relevant to our purposes, since we want to mimic the cycles seen by, and possibly caused by, short term traders. The base-case parameters for our study of retracement and projection ratios have therefore been chosen to filter out much less noise than the Pagan-Sossounov model. The initial rolling window on either side of each turning point is defined as 21 trading days (approximately one calendar month). The minimum cycle duration is defined as 42 trading days (approximately two calendar months). The minimum phase duration is set to 10 trading days (approximately two calendar weeks), unless absolute returns exceed 5%. This results in 430 identified turning points in the Dow series. Following the lead of Lo, Mamaysky and Wang (2000), a qualified technical analyst confirmed the realism of the patterns produced. However, it will clearly be necessary to test the sensitivity of any results to changes in these parameter values.

Table 3-5 – Summary statistics for bull and bear phases

Phase	Dimension	*units*	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum
Bear	Price Level	*index points*	2.9	22.6	60.8	156.5	217.6	3288.0
	log Price	*100*log price*	0.3	7.7	11.4	15.1	18.2	79.9
	% of Price	*% of price*	0.3	6.2	9.7	13.2	15.4	105.2
	Duration	*days*	3	23	42	52	64	337
Bull	Price Level	*index points*	5.6	26.0	66.1	161.0	236.8	2455.0
	log Price	*100*log price*	3.7	9.0	12.9	16.2	20.9	79.9
	% of Price	*% of price*	0.3	6.4	9.5	12.4	14.7	54.8
	Duration	*days*	7	30	50	63	75	337

The table shows statistics on the distribution of the 430 bull and bear phases identified by our heuristic from daily data on the Dow in the period January 1915 – June 2003. Note that all price changes in bear phases are negative, and the table shows their absolute values

The characteristics of the cycles are summarised in Table 3-5. Typical (median) bear phases last about 42 days, and bull phases 50 days. As would be expected given the long term upward trend in the Dow, the mean (log) return in bull phases is a little higher than in bear phases. Bear phases are also on average shorter than bull phases (52 days versus 63 days). Both price amplitude and duration are positively skewed. The mean log-return in a bull phase, for example is 15.1% as against a median of 11.4%. The picture is therefore one of a large number of relatively short-lived and small cycles and a long tail of quite long-lived bull and bear trends.

3.4. BOOTSTRAP ANALYSIS OF RETRACEMENT AND PROJECTION RATIOS

The Chapter's aim is to test a hypotheses of the form

$$R \in f \pm \varepsilon$$

where R is some ratio measured from the identified turning points in the Dow, f is a round number or Fibonacci ratio, and ε is a small bandwidth around f.

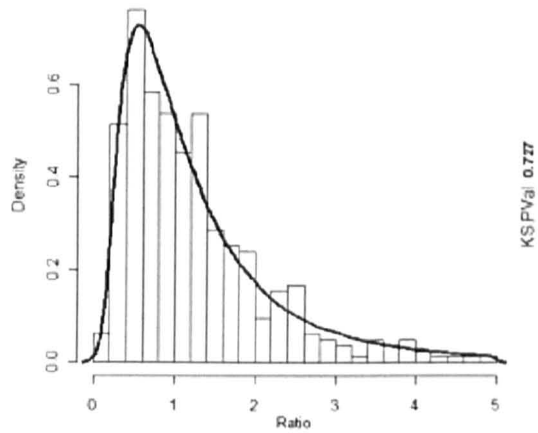
Two types of ratio R are measured, retracements and projections. Recall from the discussion of Figure 3-1 that a retracement is the ratio of one phase to the immediately preceding phase. There are therefore two types of retracement – a bull retracement when the market switches from a falling to a rising trend, and a bear retracement, when the market switches from a rising to a falling trend. A projection is the ratio of one phase to the most recent similar phase. Again, there are bull projections – the ratio of one uptrend to the previous uptrend – and bear projections. The size of the trend is measured in two ways, by price and time. A bull time projection is the ratio of the duration of one uptrend to the duration of the previous uptrend, both measured in trading days. A bull price projection is the ratio of the change in price through one uptrend to the change in price in the previous uptrend. For retracements we look at the absolute value of the price ranges, so all ratios are positive. Analysts chart prices and calculate changes in various ways. Some look at simple price bar charts. Some plot the bars on a logarithmic scale. Some calculate ratios using percentage changes rather than absolute price changes. For all price retracements and projections we have calculated the ratios in three ways, using differences in prices, differences in log-prices, and percentage differences in prices. In total we calculate 2 types (retracement and projection) x 2 trends (bull and bear) x 4 dimensions and price measures (time, and price, log price and percentage change in price) = 16 ratios.

We compare the observed values of R with the conjectured round number ratios f = 0.5, 1, 1.5, and with the Fibonacci ratios f = 0.382, 0.618, 0.786, 1.382, 1.618, 2.618 and 4.236, making 10 hypothesized values in all. Initially we look for values of R in a band in the ranges $f \pm \varepsilon$ where ε is taken as 0.025, so as to keep a clear distance between adjacent ranges.

The voluminous literature on empirical characteristic of stock returns suggests that the process driving the mean return is unstable, generally close to white noise, and punctuated by the manias and panics that lead to the best-defined bull and bear phases. There is however positive serial correlation between daily volatility, measured either by the daily price range, or by the close-to-close range. Cont (2001) provides a nice summary of these stylized facts and their implications for the returns distribution. One implication is that there is no recognizable theoretical distribution for the ratios we have calculated, so testing will have to rely on bootstrap distributions. The existence of local trends and second moment serial correlation means that a simple bootstrap is inappropriate since key properties of the returns would be destroyed by simple randomization.

Some block bootstrap method is necessary, and we have used the stationary bootstrap of Politis and Romano (1994). The pseudo-series from our sample of size n = 22194, are generated by resampled blocks, starting at a random observation number N and containing a random number of observations b, where the length of each block is drawn from a geometric distribution with a mean of p=20, the approximate number of trading days in a month. The shape of a geometric distribution dictates that whilst the mean block-size is 20 trading days, there will be large number of smaller blocks and a smaller number of blocks longer than 20 trading days. In common with the circular bootstrap (Politis and Romano, 1992), the stationary bootstrap arranges the data circularly so that P_1 follows P_n when the required block allocating a block size b starting at observation N > n-b. Unlike standard resampling or the moving blocks bootstrap, the stationary characteristics of the empirical series are maintained by the stationary bootstrap. Note that what is resampled is the whole vector of open, high, low and close prices. The resampled series thus retains the vectors four return distributions of the original series, so for example the serial correlation between successive daily ranges is approximately preserved. As with all block bootstrap methods there are discontinuities at the joins of blocks, but with our large sample size this is unlikely to bias the results.

Figure 3-4 – Bootstrap distribution of bear price level retracements



Distribution of empirical (histogram) versus bootstrap (line) price retracement ratios – the ratios of the amplitude in index points of a phase versus the preceding phase)

For each of 2000 bootstrap replications, a set of turning points is determined using our algorithm, and the corresponding values of the 16 retracement and projection ratios calculated. Figure 3-4 shows the distribution of just one of these ratios in the actual data – the bear retracement ratio in the price level – plotted against the distribution from the bootstrap experiments. If retracements were to specific levels, and were not randomly distributed, one would expect to see significant differences between actual and bootstrap distributions, with the actual data concentrated around round numbers or Fibonacci ratios. Looking at Figure 3-4 there are slightly more retracements in the ranges 0.4-0.6, 1.2-1.4 and 2.4-2.6 than suggested by the bootstrap distribution. To test formally whether there is a significant difference between these histograms, Table 3-6 shows the Kolmogorov-Smirnov (KS) p-values between each of the 16 empirical phase-ratio distributions and their relevant bootstrap distributions. Each KS p-value tests the null hypothesis that the whole distribution of each of the 16 phase-ratios does in fact match the bootstrap distribution (which in this context would suggest that nothing interesting is happening). The KS statistics fail to reject the null hypothesis of empirical and bootstrap distributions being drawn from the same distribution. The results also tend towards the probability that the empirical distributions match the bootstrap distributions. On the face of it this does not support the idea that market action causes unusual spikes in the distribution of price or duration ratios.

Table 3-6 – p-values from Kolmogorov-Smirnov tests between actual and bootstrap distributions of ratios

Phase	Dimension	Retracements	Projections
Bear	Price Level	0.727	0.458
	log Price	0.567	0.576
	Percentage price	0.634	0.838
	Duration	0.865	0.806
Bull	Price Level	0.692	0.877
	log Price	0.409	0.698
	Percentage price	0.676	0.605
	Duration	0.940	0.298

The table shows p-values for the Kolmogorov-Smirnov statistics between the distribution of each type of ratio in the Dow, and the corresponding distribution from 2000 random stationary bootstrap replications of the index series. Failing to reject the null hypothesis of a shared population distribution is not supportive of the idea that markets follow the textbook patterns examined. Values under 0.10 or 0.05 would indicate that the distributions were drawn from population distributions significantly different at the 10% and 5% levels respectively.

To test whether each specific ratio occurs more often than expected from the bootstrap distribution, we count the number of occurrences of the ratios within a band of size ε around each of the 10 hypothesized values f. The bandwidth ε has been set initially at 2.5%, and full results are set out in the following table. For each type/phase/dimension and each round number or Fibonacci ratio f we count the number of occurrences of the ratio in the interval $f \pm \varepsilon$ where $\varepsilon = 0.025$. This is compared to the distribution of occurrences in 2000 random block bootstrap replications of the index series. Table 3-7 shows the percentile of the actual number of occurrences in the bootstrap distribution. Values over 0.90 indicate significance at the

10% level, and values over .95 indicate significance at the 5% level. Discounting the results for the ratio 4.236, where there were few occurrences in the actual data or the bootstrap samples, only 15 of the 144 ratios exceed 0.90. This is only slightly more than the 14.4 that one would expect to observe under the null of equality between sample and bootstrap frequencies. Moreover, there is no consistency in the type of ratio or Fibonacci number at which these few significant results occur.

It is of course possible that our results are an artefact of the parameters of our testing procedure. We have experimented with shorter (10 day) and longer (40 day) average block lengths in our bootstrap, as against the base case of 20 days. We have also conducted tests using narrower (.01) and broader (0.05) bands around the hypothesized ratio values as against the base case value for ε of .025. None of these sensitivity tests undermine our basic, negative, result.

Our conclusion must be that there is no significant difference between the frequencies with which price and time ratios occur in cycles in the Dow Jones Industrial Average, and frequencies which one would expect to occur at random in such a time series. Our introduction noted that empirical evidence from academic studies suggests that not all of technical analysis can be dismissed prima facie. The evidence from this Chapter suggests that the idea that round fractions and Fibonacci ratios occur in the Dow can be dismissed.

Table 3-7 – Bootstrap percentiles testing retracement and projection ratios against round fraction and Fibonacci ratios

Type	Phase	Dimension	Ratios (f)									
			0.382	0.500	0.618	0.786	1.000	1.382	1.618	2.000	2.618	4.236
Retracement	Bear	Price Level	0.42	0.20	0.71	0.89	0.18	0.46	0.36	0.05	0.81	1.00**
		log Price	0.99**	0.03	0.68	0.81	0.49	0.07	0.73	0.95**	0.30	0.33
		% of Price	0.42	0.31	0.97**	0.24	0.12	0.06	0.86	0.10	0.22	0.80
		Duration	0.88	0.22	0.71	0.76	0.83	0.02	0.03	0.40	0.18	0.42
Retracement	Bull	Price Level	0.26	0.40	1.00**	0.88	0.50	0.46	0.41	0.00	0.57	1.00**
		log Price	0.95**	0.53	0.85	0.97**	0.21	0.65	0.67	0.87	0.16	0.75
		% of Price	0.14	0.06	0.94*	0.35	0.22	0.00	0.74	0.24	0.00	0.30
		Duration	0.50	0.02	0.35	0.64	0.87	0.31	0.31	0.04	0.72	0.82
Projection	Bear	Price Level	0.12	0.10	0.18	0.50	0.69	0.76	0.41	0.79	0.66	1.00**
		log Price	0.82	0.07	0.87	0.69	0.35	0.89	0.62	0.67	0.06	1.00**
		% of Price	0.41	0.65	0.54	0.88	0.64	0.00	0.50	0.75	1.00**	1.00**
		Duration	0.30	0.29	0.36	0.98**	0.78	0.13	0.89	0.08	0.64	1.00**
Projection	Bull	Price Level	0.56	0.70	0.38	0.58	0.57	0.79	0.42	1.00**	1.00**	0.43
		log Price	0.40	0.54	0.68	0.56	0.55	0.11	1.00**	1.00**	0.63	1.00**
		% of Price	0.83	0.53	0.90*	0.74	0.41	0.92*	0.63	0.81	1.00**	1.00**
		Duration	0.62	0.60	0.05	0.74	0.26	0.73	0.60	1.00**	1.00**	1.00**

For each type/phase/dimension and each round number or Fibonacci ratio f we count the number of occurrences of the ratio in the interval $f \pm \varepsilon$ where $\varepsilon = 0.025$. This is compared to the distribution of occurrences in 2000 random block bootstrap replications of the index series. The table shows the percentile of the actual number of occurrences in the bootstrap distribution. Values over 0.90 indicate significance of a textbook ratio:phase combination at the 10% level, and values over 0.95** indicate significance at the 5% level.*

3.5. APPENDICES

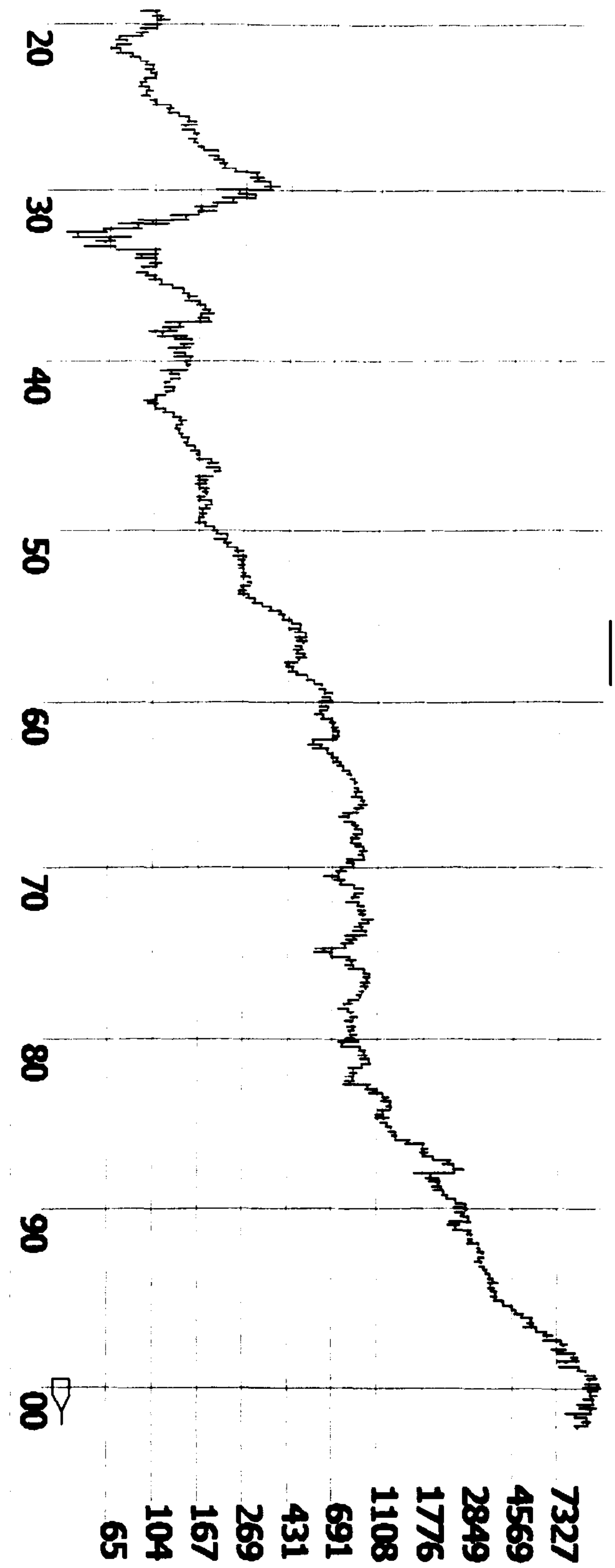
Appendix 3-1 – "Fibonacci" Ratios

"Whole Number" ratios	Phi Ascension / phi Declension	Secondary Fib Ratios
0.5*	0.236	0.786($\sqrt{\varphi}$)
1*	0.382*	1.272 ($\sqrt{\Phi}$)
2*	φ=0.618*	
	Φ=1.618*	
	2.618*	
	4.236*	

*more commonly used ratios

The ratios 0.5, 1.0 and 2.0 are not actually derived from Phi at all but are merely integer or half multiples of prior cyclical phases. These are considered by analysts along with Phi based ratios so regularly that a reference to the use of "Fibonacci ratios" would also assume inclusion of these proportions by a trader. All ratios in the second column are related by Phi (1.618) and phi (0.618), depending on whether one is ascending or descending through the ratios. The third column's ratios are mainstream but appear to be used by less analysts.

Appendix 3-2 – Dow Industrial Series 1915:2003 (logarithmically scaled)



4. PROPORTIONAL PHASE ANCHORING – TECHNICAL ANALYSIS AND BEHAVIOURIAL ANCHORING

4.1. INTRODUCTION

This Chapter tests the same proposition as Chapter 3, that the expected amplitude and duration of the next trend is not random, but depends on the amplitude and duration of the previous trend. Whilst Chapter 3 tested whether the phenomenon existed in the Dow Jones Industrials index, this Chapter examines the behaviour of individual forecasters via a survey. This proposition would suggest that forecasters "anchor" their price or duration expectations on previously observed cyclical phases. We distinguish this from other forms of time-series forecasting anchoring by calling it *proportional phase anchoring.*

The concept of anchoring is in itself not new (see Tversky and Kahneman, 1974) nor is the idea that forecasters base judgemental forecasts on preceding data. Lawrence and O'Connor (1992 and 1995) find that forecasters frequently use an anchoring-and-adjustment heuristic based on the last data point when forecasting time-series. What has not been assessed is the practitioners' claim that individuals expect phases to be proportionate to preceding phases (Hamilton, 1922, Gann, 1942, Achelis, 2000, Murphy, 2000, Pring, 1998 and Edwards and Magee, 2001).

The Chapter falls into four sections. Section 4.2 builds on Chapters 2 and 3 by providing more information about Fibonacci himself, the series that bears his name and the role of the series in the physical phenomona is examined. Section 4.3 surveys the role of proportionality in the humanities and aesthetics. The likelihood that forecasts will anchor on Fibonacci numbers or other key ratios is tested by a judgemental forecasting experiment. Subjects are presented with time series with well defined peaks and troughs and asked to forecast the next turning point. Section 4.4 introduces our judgemental forecasting survey. We develop a bootstrap method for assessing the statistical significance of specific ratios. Section 4.5 reports statistically significant ratios. It also reports the effect of forecast presentation style and the characteristics of our respondent sample on the resulting distributions of price and time ratios.

4.2. FIBONACCI AND PHYSICAL PHENOMONON

There are well defined physical contexts where Fibonacci numbers do appear. Before looking at the probability of finding these numbers in the arts and social sciences it may be useful to outline their origins. Leonardo Pisano, better known as Fibonacci, was born in Pisa in c1175 AD. He was the son of Guilielmo Bonacci, a secretary of the Republic of Pisa – hence Fibonacci, *filius Bonacci*, son of Bonacci. His father was responsible for the Pisan trading colony in Bougie, now Bejaia, in northeastern Algeria during the 1190s. Bonacci intended his son to become a merchant and had him tutored in calculation techniques. In time Fibonacci was engaged in business in Egypt, Syria, Greece, Sicily, and Provence for the Pisan republic. This provided Leonardo with the opportunity to study mathematical techniques used across these regions.

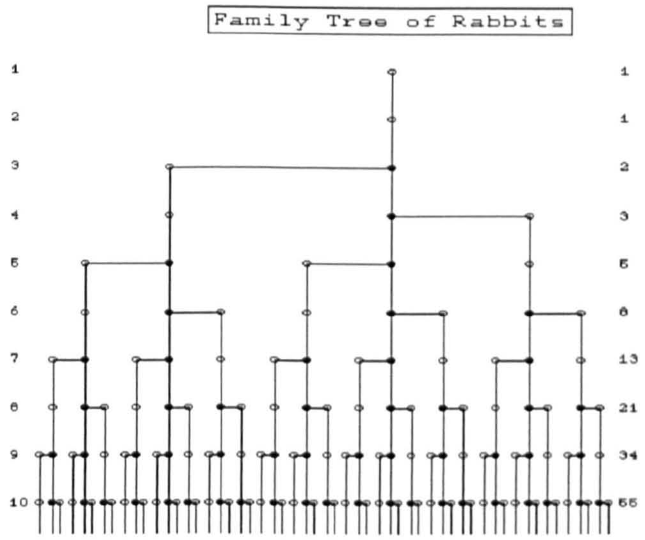
Fibonacci returned to Pisa in c1200 where he worked on his own writings for around a quarter of a century. Despite *Di minor guisa,* examining commerical arithmetic, and his commentary on Euclid's *Elements* being lost, Fibonacci's more abstract theoretical legacy is still well recognised. Yet it was the practical applications of his work that brought Fibonacci fame amongst his contemporaries and his wider contribution is not well known. *Practica geometria* (Pisano, 1220) was a collection of geometric problems based on Euclid's *Elements* and *On Divisions,* such as calculating the sides of geometric shapes using the diameter of circumscribed or inscribed circles, for example. These came with precise proofs and practical information for surveyors, including a chapter on how to calculate the height of tall objects using similar triangles. *Flos* (Pisano, 1225) addressed some of the challenges highlighted by Omar Kyahham's algeraic treatise. *Liber quadratorum* (Pisano, 1225) was arguably Fibonacci's most remarkable work, yet it was not widely read, and addresses number theory, examining Pythagorean triples calculations for example.

Nevertheless, the work that left the most personal mark on mathematics was Fibonacci's earliest major work, *Liber abaci* (Pisano, 1202). This is presumed to have introduced the Hindu-Arabic decimal system to Europe (more conducive to calculations than Roman numerals), simultaneous linear equations, irrational numbers and accounting issues and currency conversion for merchants.

It is the third section of *Liber abaci* that introduced the series of numbers that now bears Fibonacci's name. A number of problems were used to illustrate the role of the sequence, including the famous rabbit reproduction problems where somone puts a pair of rabbits in an enclosure. "*How many pairs of rabbits can be produced from that pair in a year if it is supposed that every month each pair begets a new pair which from the second month on becomes productive?*" (Pisano, 1202)

The first pair mate at the end of the first month (1 pair total) but their pair is only born at the end of the second month (now 2 pairs). At the end of the third month the original female produces a second pair (3 pairs). The close of the fourth month brings another two pairs, from both the original female and the female born two months ago (5 pairs). This growth is illustrated by Figure 4-1.

Figure 4-1 – Fibonacci Growth of Rabbits (Knott, 2003)



So the number of pairs of rabbits at the start of each month increases as follows: 1, 1, 2, 3, 5, 8, 13, 21, 34, etc. Each number in this sequence is the sum of the preceding two. Fibonacci provided other similar examples and problems that demonstrate the role of the series and the series provides the basis for many simple numerical puzzles. There are many interesting properties exhibited by the Fibonacci series itself. If one examine the final digits of the numbers in the series one sees that these repeat themselves after 60 numbers in the series, a cycle length of 60. For the last two digits the cycle length is 300, the last three digits the cycle length is 1,500, the last four digits the cycle length is 15,000, the last five digits 150,000. The initial digits of the numbers in the Fibonacci series are governed by Benford's law (Benford, 1938 and De Ceuster, Dhaene and Schatteman, 1997), in the same way that some natural phenomena and randomly chosen integers/real numbers are.

For further examples of the many mathematical points of interest of Fibonacci see Knott (2003) – cited as the leading resource by the Fibonacci Association. If one takes the ratio of a number in the Fibonacci series versus the immediately preceding number one find that the ratio has some interesting properties. The ratios stabilise by approximately the fifth number in the Fibonacci series and remain accurate to fifteen decimal places after the fortieth number in the series. This irrational number has been given many names over the centuries: Φ (Phi), the golden mean, the golden ratio, the golden proportion, the golden section or even the divine proportion or divine section. A ratio of φ (phi) is found if one instead descends down the sequence, 0.618034... Between alternate numbers in the sequence, the ratio is approximately 0.381966 (0.618034^2). Phi is the only number that when added to 1 produces its inverse, phi.

The Fibonacci series is also of interest to scientists beyond its purely mathematical properties. There appears to be a significant tendency for anatomy of plants to be governed by Fibonacci numbers (Knott, 2003). There are many species which consistently have a precise number of petals they have, for example buttercups, whilst many others have petals that are very close Fibonacci numbers, with the asymptotic mean being a Fibonacci number. The number of clockwise and anti-clockwise rotations before meeting a leaf directly above the first tends towards Fibonacci numbers, as do the number of leaves that are passed along the way. There is also tendency for these three numbers to be consecutive Fibonacci numbers. The evolutionary reason for this phenomenon is that Phi provides the single optimal fixed angle of rotation for exposure of flowers or petals to light and insects, whilst allowing for optimal soil exposure for rain.

Furthermore, this also provides a fixed angle of rotation between new cells or seeds, with uniform packing that can be maintained at any stage of plant growth, even when the final number is unknown. Pinecones and cauliflowers, for example, also show the golden (Phi proportioned) spirals clearly. The number of turns in each set is a Fibonacci number, and this avoids overpopulating the centre or underpopulating the edges (Brousseau, 1968 and 1969, also see Onderdonk, 1970, Davis, 1970 and 1971). The shape of cells or seeds dictates the optimal packing formation of a *defined* number of cells. But Phi appears to solve the problem of maintaining optimality as a plant grows to an *undefined* number of cells. Douady and Couder (1993) prove this optimal stacking theorem mathematically.

There is also a literature that suggests that on average human anatomy is proportioned according to Phi. Kawakami and Tsukada (1989) documents some of the Phi based relationships that appear to define human facial attractiveness. The ratio of the distance between our eyes to the width of the eyes themselves tends towards the golden section, for example. As seen from the front, the width of one's central incisor is in the golden proportion to the width of the lateral incisor. This relationship continues as the lateral incisor is in the same proportion to the adjacent canine and this in turn is proportional to by Phi to the first premolar. These asymptotic tendencies are also found as a golden rectangle in human front teeth; the height of the central incisor is the width of the two central incisors (Levin, 1978). There is even a literature that Phi proportions the cycles exhibited by a healthy heart beat and brain wave cycles (Weiss, 1992; Weiss and Weiss, 2003). These physical manifestations are interesting, but it must be noted that whilst the Fibonacci series and Phi appear in various natural phenomenon, they are not the only such numbers. All that can be said is that this intriguing natural pattern is *"not a universal law but only a fascinatingly prevalent* *tendency"* (Coxeter, 1961).

4.3. HUMANITIES, AESTHETICS AND JUDGEMENTAL FORECASTING

There is a consensus about the role of Phi in nature. Whether Phi plays a role in aesthetic preferences is more controversial. Facial attractiveness appears to depend on possession of average and symmetrical features, and Kawakami and Tsukada (1989) document some of the Phi based relationships that appear to define human facial attractiveness. Ekman, Friesen and Ellsworth (1982) show that the importance that we place on the face when interpreting and judging others does not differ culturally. Mainstream dental aesthetics reading for dental and orthodontic students also includes Phi based relationships (Levin, 1978).

There is some evidence of conscious use of Phi in the humanities, but this is not necessarily the same as an innate aesthetic preference. This controversy is at the heart of understanding how or whether market participants anchor cyclical phases on prior phases. It could be the case that chart analysts anchor in Fibonacci ratios because they "look right".

Livio (2002), Knott (2003) and O'Connor and Robertson (2003b) document the role of Phi in two-dimensional geometry and Platonic solids. Basic shapes proportioned using Phi, such as the rectangles, triangles or spirals, have often been the starting point for artists when proportioning their works. Weiss (1992) suggests that Phi plays in handwriting, the formation of which becomes more automatic as one matures. However, many such speculative examinations of the occurrence of phi are derived from wishful thinking, visual "data mining", or even a judicious choice of where exactly to start measuring from. Claims about its use in structuring the Pyramids and the Parthenon, for example, are not easily verifiable due to both ruin and erosion. The ancient Greeks were aware of Phi but did not write of it as pleasing or beautiful. The idea did exist by the Renaissance, but only took hold by the late 1800's. Moreover, erroneous occurrences of Phi can be observed when measuring and averaging values in inappropriate contexts (Fischler, 1981). Nevertheless, there are a number of artists who have used Phi explicitly. Phi based proportions have been implemented explicitly by artists and designers throughout the ages from Islamic art, Da Vinci's works, Mondrian's Rectangles, Picasso's Post through to the architect Le Corbusier. Occurrences of Phi intrigued Jacob Bernoulli to the extent that he had a golden spiral, a Phi based growth curve, etched on his gravestone and Isaac Newton had one etched on his bed headboard. The debate about the status of ϕ in art is summarised in the entertaining and informative monograph of Livio (2002).

The application of golden proportion has also extended into musical composition. Kay (1996) reports an analysis of Mozart's sonatas, finding that they are composed of two sections, divided exactly at the golden section in nearly every case (see Putz, 1995 for more information on Mozart and Phi). Whether or not this was a conscious choice or intuitive application is not known, but Mozart's fascination with mathematics has been well documented. Haylock (1978) states that the well known opening of Beethoven's Fifth Symphony appears at the beginning and end of the piece, and it also repeats exactly 0·618 (phi) of the way through the symphony and at the start of the recapitulation, 0·382 ($= 0.618^2 = 1-0.618$) of the way through.

Do artists use Phi proportions because they are in some sense innately "pleasing"? The aesthetic preferences literature has examined how pleasing respondents found differently proportioned shapes and sets of lines presented to them.

The pioneering psychologist Gustav Fechner (1876) conducted experiments that seemed to show that people had preferences for rectangles with sides approximately in the ratio 1:ϕ. Criticisms have been made of his methodology, but Green (1995) argues that most of these are based on flawed translations from German. Benjafield (1976) and Piehl (1978) also draw supportive conclusions and McManus (1980) finds "moderately good evidence for the phenomenon which Fechner championed". Nevertheless the evidence is certainly not overwhelming or consistent. Davis (1933) asked respondents to draw "pleasing" rectangles, as opposed to selecting them from a set, but only 3% of the Davis (1933) subjects drew the golden rectangle. The idea was also strongly challenged by Godkewitsch (1974), who found that respondents preferred shapes proportioned by equality. Green (1995) critiques both the advocates and the critics, pointing out that results have regularly been followed by contradictory work that accounts for recent criticisms. In short, if it exists, any Phi effect is certainly fragile.

Interestingly, there do appear to be patterns as to when suggestive evidence arises. Thompson (1946) concurred with Titchener (1899)'s belief that younger people prefer equality and preference for asymmetric shapes develops with age. However, Thompson was perplexed by the "nonverbal transmission" of the idea of the golden section since the majority of his subjects "had never even heard of the golden section." He assumed that they must have been following subconscious cultural norms, since nothing in the psychological literature suggested that shape preferences followed innate behaviour (Green, 1995). Berlyne (1970) did find a general cultural effect on aesthetic preferences of Japanese versus Canadian high-school girls. The Japanese children had a clear preference for squares or near square rectangles whereas the Canadians preferred Phi shapes. Berlyne (1971) later noted that the golden section has historically been an element of the "Mediterranean civilizations and their offshoots." Although the point was not made in the context of culture, Piehl (1978) also notes that subjects more familiar with the golden rectangle came to prefer it.

The idea of an aesthetic preference for equality is of direct interest to our work. As discussed in Chapters 2 and 3, the practitioners' literature on technical analysis claims that turning points can occur at ratios such as 0.5, 0.618 or 1 times a preceding phase. Hamilton (1922), for example, asserts that 50% is the "typical amount", as if some kind of aesthetic balance has been reached. Whilst it is patently subjective to the point of being untestable (Mandelbrot, 1999), Fibonacci based Elliott Wave analysis is far from uncommon in industry.

4.4. DATA AND EXPERIMENT DESIGN

The contribution to the literature by this Chapter is based on a judgemental forecasting survey of sixty MSc students matriculated on specialist finance postgraduate degrees at Cass Business School in the City of London. To identify the characteristics of our sample, the respondents were first asked to complete the form in Figure 4-2. This asked a number of questions including age, gender, pre-MSc country of study, a breakdown of experience in the finance industry and opinions about technical and fundamental analysis. As well as providing an understanding of our sample, this data allows us to compare the forecasts made by groups with shared different ages, cultural backgrounds and other characteristics.

Figure 4-2 – Respondents' Survey Form

Please answer the following questions:

1) Name: ....

2) MSc: ....

3) Age: ....

4) Gender: Male [ ] Female [ ]

5) Pre-MSc country of study: ....

6) Have you ever worked in the finance industry?

Yes [ ] No [ ]

If yes, which markets?

Equities	Index Futures	Non-energy Commodity Futures	Energy Futures	Foreign Exchange	Government Debt	Corporate Debt
[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

How much did you know about technical analysis before this elective?

Nothing at all	Very little	Some knowledge	Expert
[ ]	[ ]	[ ]	[ ]

Before starting this elective, what was your opinion about the usefulness of technical analysis?

Completely useless	Probably useless	No opinion	Sometimes useful	Always useful
[ ]	[ ]	[ ]	[ ]	[ ]

Before starting this elective, what was your opinion about the usefulness of fundamental analysis?

Completely useless	Probably useless	No opinion	Sometimes useful	Always useful
[ ]	[ ]	[ ]	[ ]	[ ]

Before starting this elective, how did you think practitioners mixed technical analysis with fundamental analysis?

All fundamental	Mostly fundamental	No opinion	Mostly technical	All technical
[ ]	[ ]	[ ]	[ ]	[ ]

Each respondent was given one of two survey packs and asked to make forty forecasts, a total of eighty unique forecasts across both groups. The time series for each forecast showed four turning points. Respondents were told to assume that the series would reverse at the final turning point and they should identify the next turning point in the data.

Twenty unique random walks were used for the series in the survey – ten of these terminating at a peak and ten at a trough, generated with the same noise parameter for each trough/peak pair. An equal number of peaks and trough series were thus presented.

There is clear evidence that different presentation formats can affect the accuracy of forecasts (Lawrence, 1983, Lawrence, Edmundson and O'Connor, 1985 and Harvey and Bolger, 1996). Moreover, aesthetic preferences would depend on graphical presentations of data rather than tabular data. We therefore present each series in four different forecast styles, giving the total of eighty forecasts. These include the series being plotted with:

1) unscaled axes;

2) scaled axes (daily frequency);

3) scaled axes (daily frequency) with a table of the primary turning points; and

4) only the table of turning points and no graphical presentation.

Figure 4-3 shows the written instructions given to the respondents and examples of the building blocks of each forecast style. For the first three forecast types the forecaster is asked to write a cross on the graph at the time and price of the next turning point. The final tabular forecast style requires a written date and price.

The 80 (= 20 series x 4 format style) charts were split across the two packs to ensure respondents made forecasts for each series in two different formats. Both packs had an equal number of each style of presentation. This caters for the guidelines of Harvey and Bolger (1996) with regards to balanced within-subject design, consistency in altering presentation and the use of a variety of series so as to not be hostage to idiosyncratic features of series. The structure and contents of the survey packs attempts to avoid a number of other potential biases. We avoided framing the forecast phase gradient by stating that a reversal is to occur at the end of the series. Care was also taken so that the axes did not frame responses within tight visual boundaries. It is unlikely that respondent recognition of the same series in the alternative format would have affected the results. The half an hour given is unlikely to have allowed sufficient time for respondents to make the associations across forty forecasts. Many of these series will also have been redisplayed only in a tabular format, which provides further reassurance.

Before filling in the survey, the students were read a verbal set of instructions a number of times (Figure 4-4). As in Lawrence & O'Connor (1992), they were told clearly that they were being presented with financial time-series and also that a prize of a bottle of champagne was to be awarded to the "winner". The intention was to motivate serious forecasting based on how the students believed financial time series behave. There could be no "correct" answers as the students were presented with random walks and so the winner was in fact selected randomly.

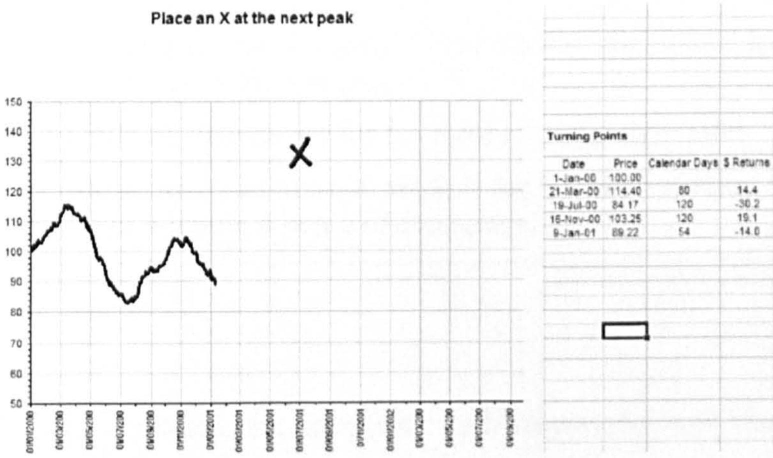
Figure 4-3 – Survey Instructions

<u>Forecasting Turning Points</u>
You will now be asked to make two types of forecasts of turning points for several price series: Graphical forecasts based on charts of cycles in security returns, Numerical forecasts based on tables of cycles in security returns.
Turning points in security X's returns have been identified on each diagram/ table.
Assume that X's price reverses direction exactly at the final turning point.

<u>Instructions (Graphical Forecast)</u>
Mark a cross on the page at the date and price of where you believe the next turning point will be.

DO NOT mark the chart in any other way i.e. do not draw any lines, etc.

Example:



<u>Instructions (Numerical/Tabular ONLY Forecast)</u>
Write the date and price of where you believe the next turning point will be.
Write the month ALPHABETICALLY e.g. 12th September 2002 (NOT 12/9/02)

Example:
Turning Points

Date	Price	Calendar Days	$ Returns
1-Jan-01	37.00		
1-May-01	45.00	120	8
1-Mar-02	39.00	304	-6
1-Sep-02	62.00	184	23

Forecast the Next Peak

Date	Price
01-Sep-03	56

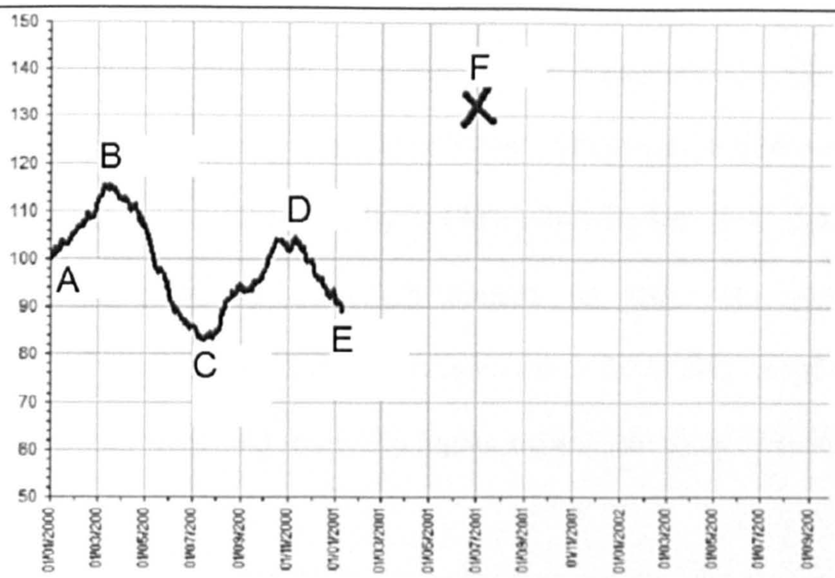
Figure 4-4 – Verbal Survey Instructions

> We are asking you to take part in a study of intuitive forecasting of turning points in financial time series. This is not an assessment. But there will be a bottle of champagne for the most accurate forecaster.
>
> First, fill in the cover sheet with some personal details.
>
> You then have to make a series of forecasts.
>
> Some are graphical. You should mark an "X" where you think the next turning point will occur.
>
> Some are tabular. You fill in the date and level at which the next turning point will occur. You must write the month alphabetically e.g. 12^{th} September 2002. NOT 12/9/02 or 9/12/02
>
> Do not spend too long on the forecast. You should aim spend less then 10 seconds on average for each for forecast.
>
> There will be a bottle of champagne for the most accurate forecaster.
>
> This is not an assessment you are not marked for it. BUT putting your name you have a chance of winning a bottle of champagne.

After the task was completed, the data from each respondent was transferred from paper to a relational database, to ensure data consistency and flexible data pooling and extraction. Structured query language (SQL) is the standard relational database query language and allows for flexible extraction from datasets. Our SQL code was called seamlessly from our database engine directly from our coded statistical environment.

The calculation of phase ratios for both the graphical and tabular forecasts was performed in SQL. These ratios were then pooled differently for different analyses. Firstly, the eight individual phase ratios for each graphical forecast type were pooled. The three graphical forecast types and eight ratio types thus gave 24 datasets, each of which contained a specific ratio for a specific forecast format pooled across all respondents. Figure 4-5 documents the eight different phase ratios.

Figure 4-5 – Specific Phase Ratios



Amplitude of the forecast phase | F-E | versus the amplitude of
1) the entire series | B – C |
2) the preceding phase | D – E | (the price retracement)
3) the penultimate phase | D – C | (the price projection)
4) three phases previously | B – A | (an alternative price retracement)

Duration of the forecast phase | F-E | versus the duration of
5) the entire series | E – A |
6) the preceding phase | E – D | (the duration retracement)
7) the penultimate phase | D – C | (the duration projection)
8) three phases previously | B – A | (an alternative duration retracement)

4.5. RESULTS

Table 4-1 details the profile of respondents form their completion of the background survey preceding the forecast survey.

It shows that around 40% of our sample were students pursuing the more quantitative specialist Masters degrees. Our sample received their pre-MSc education in 17 different countries. 53% of the respondents stated that their pre-MSc education was

British. The next largest groups were those educated in China (8%) or Greece (7%). 78% of the students were under 30 years of age and 48% were under 25 old. 68% of the sample had work experience in the finance industry, with a strong focus on equities, government bonds and corporate bonds respectively. There was no experience in commodities or energy and only few with foreign exchange experience, the dominant domain of technical analysis (Allen and Taylor, 1992; Lui and Mole, 1998). The perception was that practitioners do mix both technicals and fundamentals. Whilst nobody believed that technical or fundamental analyses were of no use, fundamentals were held in slightly higher regard, and more consistently so.

Table 4-1 – Sample Profile

Country of Pre-MSc Education Profile of Sample

Pre-MSc_Country	Percentage	Count
Britain	53%	32
China	8%	5
Greece	7%	4
America	5%	3
India	5%	3
Canada	3%	2
Argentina	2%	1
Azerbaijan	2%	1
Germany	2%	1
Italy	2%	1
Pakistan	2%	1
Russia	2%	1
South Africa	2%	1
Spain	2%	1
Tunisia	2%	1
Turkey	2%	1
Venezuala	2%	1

Age Profile of Sample

Ages	Frequency	Count
21-24	48%	29
25-29	30%	18
30-34	15%	9
35-39	5%	3
40-45	2%	1

Degree Profile of Sample

Degree	Percentage	Count
MSc Investment Management	52%	31
MSc Mathematical Trading and Finance	30%	18
MSc Financial Economics and Econometrics	5%	3
PhD in Finance	5%	3
MSc Financial Management	3%	2
MSc Banking and International Finance	2%	1
MSc Energy, Trade and Finance	2%	1
MSc Finance	2%	1

Experience Profile of Sample

	Commodities	Corporate Bonds	Energy	Equities	Forex	Government Bonds	Index Futures
Percentage	0%	13%	0%	27%	7%	20%	2%
Count	0	8	0	16	4	12	1

Opinion Profile of Sample

	Technical Analysis Knowledge	Opinion of Technical Analysis	Opinion of Fundamental Analysis	Belief re: Industry TA & Fundamental Mix
Max	4.00	5.00	5.00	4.00
Min	1.00	2.00	2.00	2.00
Mean	2.22	3.68	4.27	2.67
Median	2.00	4.00	4.00	3.00
SDev	0.78	0.77	0.69	0.73

Technical Analysis Knowledge (scaled 1-4, 1 = no knowledge, 4 = expert)
Opinion of Technical Analysis (scaled 1-5, 1 = low opinion, 5 = high opinion)
Opinion of Fundamentals Analysis (scaled 1-5, 1 = low opinion, 5 = high opinion)
Opinion of how Technical and Fundamental Analysis are mixed in practice (scaled 1-5, 1= All Fundamentals, 5 = All TA)

We were initially interested in whether or not the volatility of the series drove forecast amplitude or duration. It might be expected a priori, but the relationship did not appear to exist (Table 4-2).

Table 4-2 – Series Volatility versus Forecast Phases' Amplitudes and Durations

$ForecastAmplitude_f = \alpha + \beta\sigma_F + \varepsilon_f$ *where f is the respondent forecast and F is the series corresponding to forecast f*

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.23	1.79	-0.13	0.90
SDevSeries	0.30	0.20	1.49	0.14

Residual standard error: 25.49
Multiple R-Squared: 0.00049, Adjusted R-squared: -0.00027
F-statistic: 0.657 on 1 and 1320 DF, p-value: 0.422

$ForecastDuration_f = \alpha + \beta\sigma_F + \varepsilon_f$ *where f is the respondent forecast and F is the series corresponding to forecast f*

Coefficients:

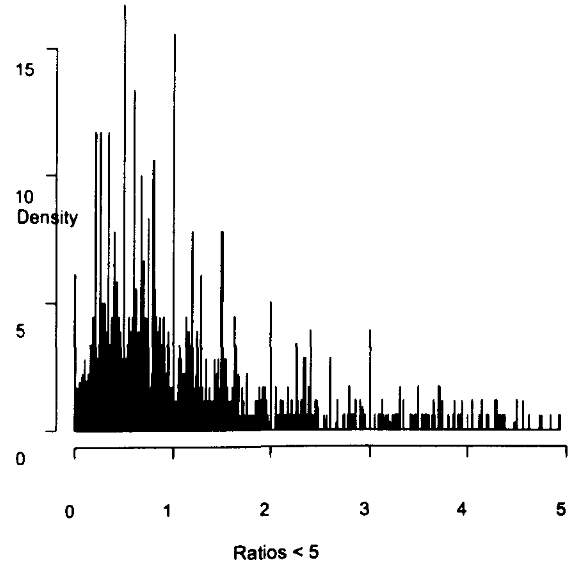
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	29.97	1.33	22.51	<2e-16 ***
SDevSeries	0.0083	0.15	0.056	0.96

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 21.97
Multiple R-Squared: 5.797e-05, Adjusted R-squared: -0.0007
F-statistic: 0.0765 on 1 and 1320 DF, p-value: 0.782

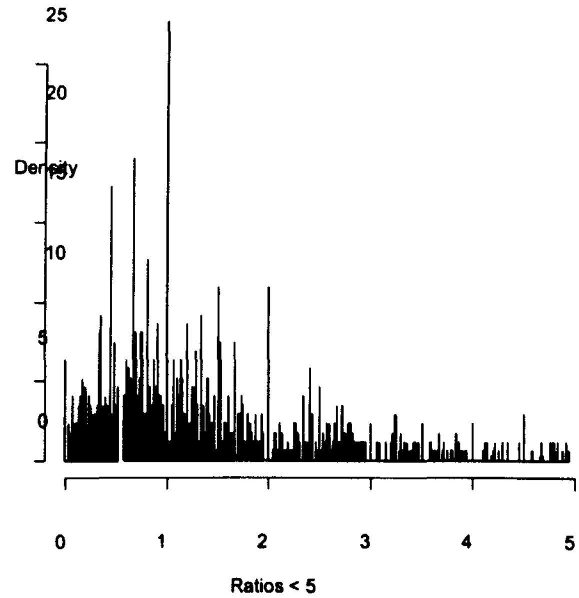
Appendix 4-1 and Appendix 4-2 provide a summaries of ratios for each survey style and broken down further for each phase ratio per style. Nothing of note can be interpreted from these summaries of the distributions, yet the plot of ratio distributions in Figure 4-6 reveals the dominance of whole number ratios for each amplitude ratio across all forecast styles – with the ratio 1 strikingly consistent. There were only two most frequent ratios which were not 1. When comparing forecast phase amplitude versus the amplitude of the series, the 50% ratio is most frequent. 50% price retracements also stand out in frequency, consistent with technical analysis textbooks. These two occasion of 50% ratio dominance were closely followed by a ratio of 1 as the second most frequent ratio. Figure 4-7 illustrates duration ratios across all forecast styles. The same whole number pattern dominates, except for the ratio of the duration of the forecast phase versus the whole series. Both the distributions of amplitude and duration ratios strongly suggest that the ratio of 2 is of interest.

The same occurs in Figure 4-8, but only the three chart-based styles follow this pattern, despite the tabular forecast ratios being closest to the chart-plus-table by KS p-value (see below). Table 4-3 shows the two ratios with the highest densities for each forecast style, but broken down by both style and phase. A similar whole number pattern emerges. Ratios of 1 and 2 clearly dominate the rankings of both most frequent and second most frequent ratios from the respondents' forecasts.

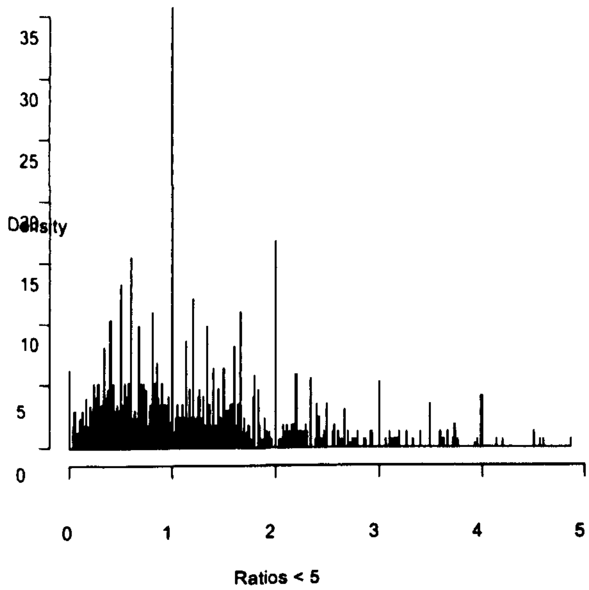
Figure 4-6 – Amplitude Distributions (with reference to Figure 4-5's phase lettering)



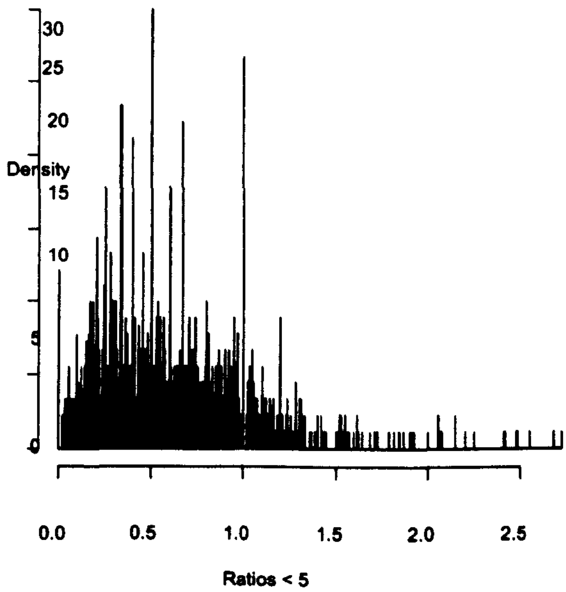
Retracements of Amplitude $|D - E|$



Projections of Amplitude $|D - C|$

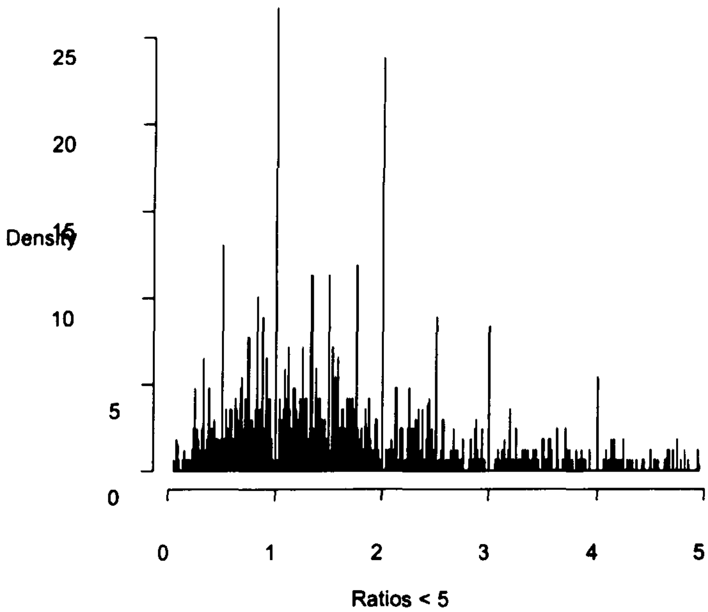


Retracement of Amplitude Three Phases Previously $|B - A|$

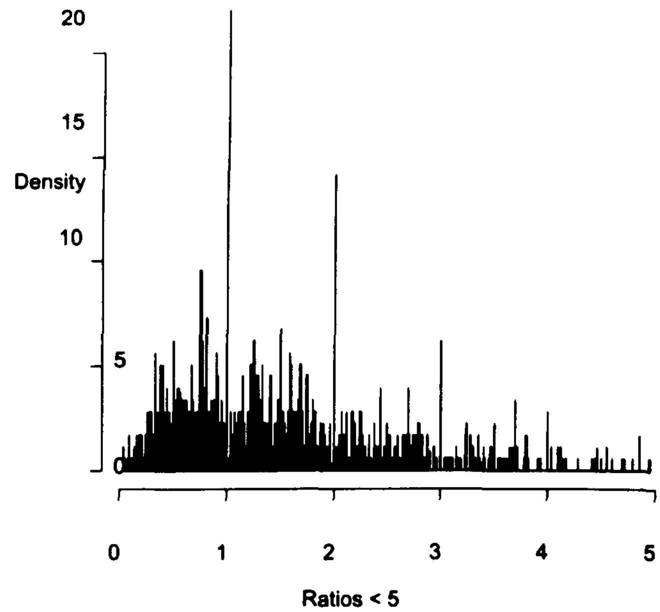


Ratio versus Series Amplitude $|B - C|$

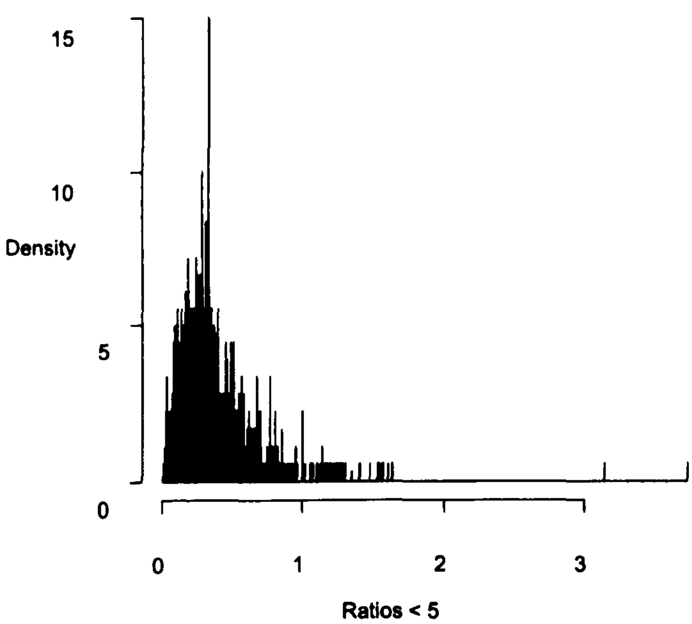
Figure 4-7 – Duration Ratio Distributions (with reference to Figure 4-5's phase lettering)



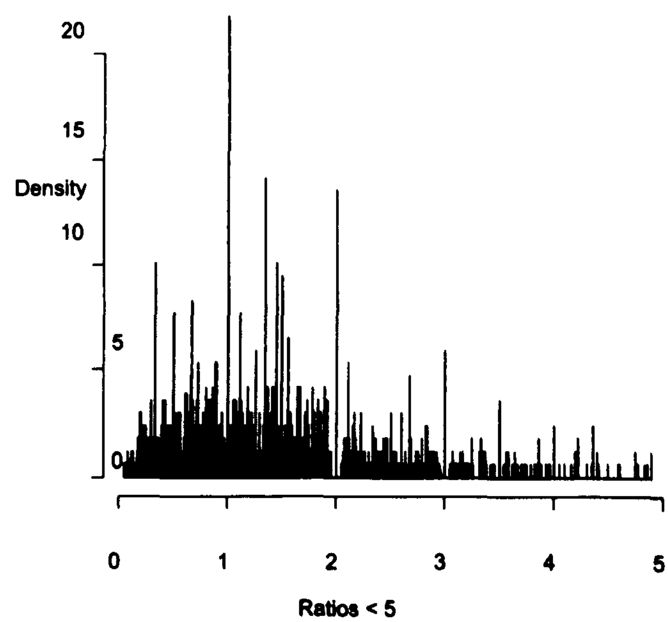
Projections of Duration | $D - C$ |



Retracements of Duration | $E - D$ |

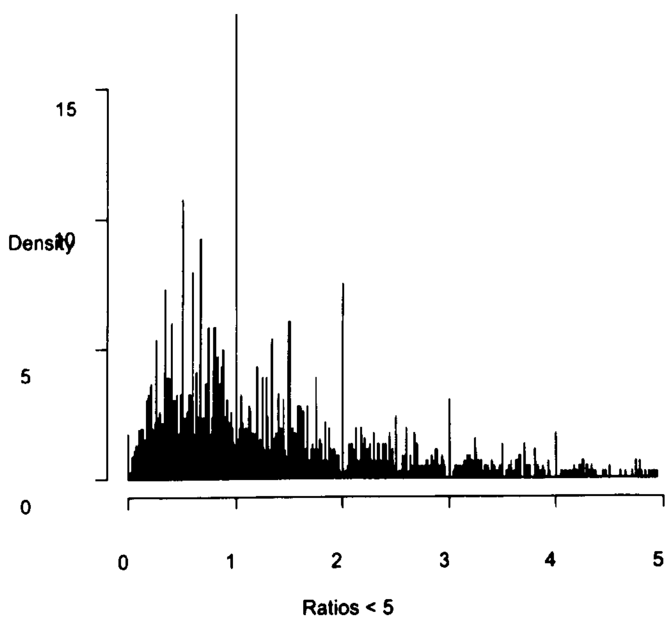


Ratio versus Series Duration | $E - A$ |

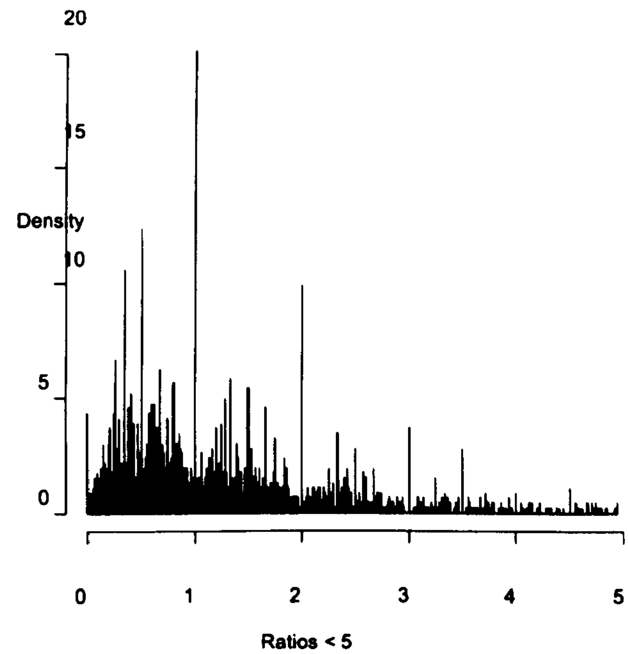


Retracement of Duration Three Phases Previously | $B - A$ |

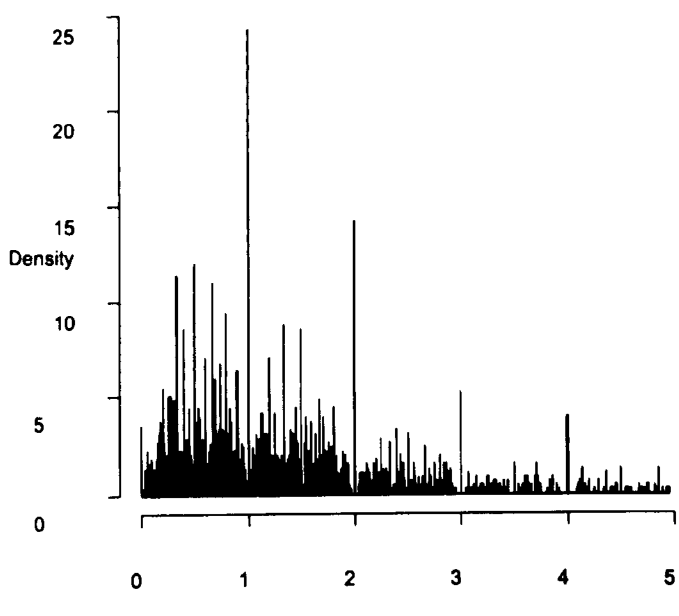
Figure 4-8 – Ratios Distributions for Forecast Styles



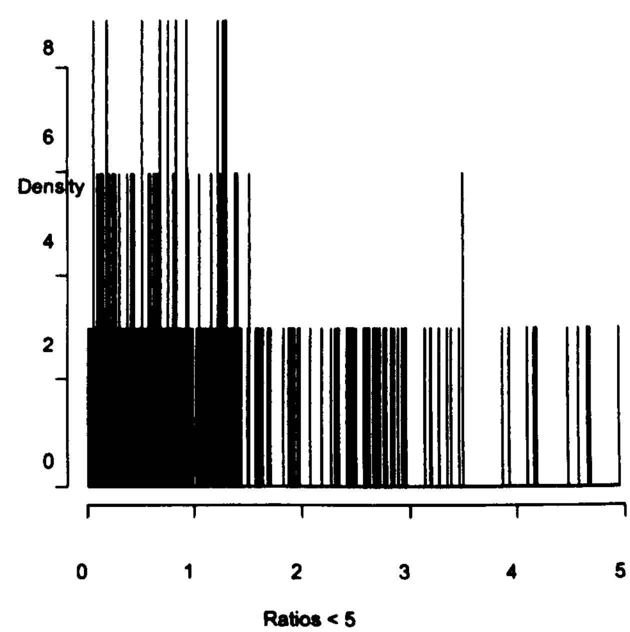
Bare Chart Ratios



Scaled Chart Ratios



Chart+Table Ratios



Tabular Ratios

Table 4-3 – Ratio with maximum densities per phase

Unscaled Chart - Amplitude/Price Anchoring	Max	2ndMax
Vs. Series	0.515	0.245
Retracement	0.355	0.49
Projection	0.995	0.665
Altern. Retracement	0.595	0.99
Unscaled Chart - Duration Anchoring		
Vs. Series	0.18	0.19
Retracement	0.995	0.79
Projection	0.995	1.985
Altern. Retracement	0.995	0.705

Chart-plus-Table - Amplitude/Price Anchoring	Max	2ndMax
Vs. Series	0.445	0.395
Retracement	0.695	0.495
Projection	0.995	0.665
Altern. Retracement	0.995	1.99
Chart-plus-Table - Duration Anchoring		
Vs. Series	0.285	0.325
Retracement	0.995	1.99
Projection	0.995	1.99
Altern. Retracement	0.995	1.43

Scaled Chart - Amplitude/Price Anchoring	Max	2ndMax
Vs. Series	0.115	0.49
Retracement	0.195	0.555
Projection	0.995	0.795
Altern. Retracement	0.995	0.495
Scaled Chart - Duration Anchoring		
Vs. Series	0.085	0.21
Retracement	0.995	0.37
Projection	0.995	1.99
Altern. Retracement	0.33	0.99

Tabular - Amplitude/Price Anchoring	Max	2ndMax
Vs. Series	1.158	0.432
Retracement	1.215	1.085
Projection	1.29	1.11
Altern. Retracement	0.36	1.03
Tabular - Duration Anchoring		
Vs. Series	0.06	0.058
Retracement	0.14	0.595
Projection	0.92	0.29
Altern. Retracement	1.205	1.505

To test formally whether some ratios occur significantly more frequently than others we develop a novel test based on bootstrapping residuals from a kernel density estimator fitted to the empirical phase ratio distributions.

Firstly, a kernel density estimator (KDE) was fitted to each of the eight phase ratio distributions for the three chart styles. There are a number approaches to smoothing an empirical distribution to estimate the distribution from which it is drawn. Simple approaches from moving averages, whether basic or exponential, though to polynomial smoothing may be used. KDEs provide a primary accepted means for estimating a population distribution (Parzen, 1962). The KDE algorithm disperses the mass of the empirical distribution function over a regular grid and then uses a fast Fourier transform to convolve this approximation with a discretized version of the kernel. Linear approximation is then used to evaluate the density at the specified points.

Secondly, the residuals of each KDE were then resampled with replacement 2000 times to provide us with a p-values for the the expected frequencies of each ratio. Based on these resampled distributions, we computed 95% confidence interval for the number of ratios found within bands of $\pm\ \varepsilon$ around the hypothesised ratios of 0.382, 0.5, 0.618, 0.786, 1, 1.382, 1.618, 2, and 2.618, where the band width is variously set at $\varepsilon = 0.005$, 0.01, 0.025 and 0.05. This allows the examination of whether ratios cluster very tightly around 0.5, say in the range 0.495 to 0.505, or whether they are scattered in the more diffuse range 0.445 to 0.555.

This impact of whole numbers is corroborated by our KDE bootstrap test on the chart based forecasts. Table 4-4 shows those ratios which are significant at the 5% level when pooling together the ratios for each forecast style regardless of phase. The only two ratio densities greater than their 95% confidence levels are 1 and 2. This is consistent across all forecast styles. Table 4-5 shows the results of the KDE bootstrap when we also examine the ratios for each phase. From the most frequent anchoring ratios that we saw previously (Table 4-3), we see that ratios 1 and 2 again dominate the per phase KDE bootstrap results of Table 4-5. The ratio 0.5 is significant in only one case, for duration projections in full information forecasts.

Table 4-4 – Ratios significant at 5% level (by Survey Style)

Bare Chart

Ratio	Band	KDE Bootstrap Stat
1	0	0.80**
2	0	5.17**

Scaled Chart

Ratio	Band	KDE Bootstrap Stat
1	0	5.05**
2	0	10.16**

Full Info Chart

Ratio	Band	KDE Bootstrap Stat
1	0	3.87**
2	0	14.46**

KDE Bootstrap Statistic: 0 = Critical Value for 95% Confidence Level

There are a number of other interesting observations that can be made from the KDE bootstrap results in Table 4-4 and Table 4-5. Firstly, when we pooled anchored ratios by style (Table 4-4) only a band of 0 led to statistical significance. Moreover, it is interesting that band values of 0 dominate significance of a breakdown of the individual ratios (Table 4-5). This same phenomenon was found when determining the number of bins to plot the distributions on page 103 – 1% bins were used as any less did not show the whole number ratio phenomenon which existed across all chart based forecasts. This means that respondents not only anchor their forecast phases on previous phases, but that they do so more precisely that might be expected. Secondly, there is support for our hypothesis of a general anchoring of phases *separately and in addition* to anchoring on support or resistance from previous extremes. This is important because frequent *amplitude* anchoring of a ratio 1 could often be dismissed as only support or resistance from previous extremes. Nevertheless, we can definitively dismiss the suggestion that we are only witnessing a support or resistance effect, due to the greater significance of the ratio 2 in the KDE bootstrap tests and because anchoring also occurs in the *duration* of phases.

Table 4-5 – Ratios significant at 5% level (by Survey Style & Specific Ratios)

Unscaled Chart - Amplitude/Price Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
1	0	1.29	Altern. Retracement
2	0	0.18	Vs. Series
2	0	0.29	Projection
2	0	1.66	Altern. Retracement

Bare Chart - Duration Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
1	0	0.10	Vs. Series
1	0	1.37	Retracement
1	0	0.11	Projection
1	0	1.64	Altern. Retracement
2	0	0.34	Vs. Series
2	0	0.70	Retracement
2	0	1.70	Projection
2	0	0.80	Altern. Retracement
2.618	0	0.34	Vs. Series
2	0.01	0.34	Vs. Series
2.618	0.01	0.34	Vs. Series
2	0.025	0.34	Vs. Series
2.618	0.025	0.34	Vs. Series
2	0.05	0.34	Vs. Series
2.618	0.05	0.34	Vs. Series

Scaled Chart - Amplitude/Price Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
1	0	0.32	Projection
1	0	2.62	Altern. Retracement
2	0	0.25	Retracement
2	0	0.38	Projection
2	0	1.54	Altern. Retracement
2.618	0	0.26	Vs. Series
2.618	0	0.44	Retracement
2.618	0.01	0.26	Vs. Series
2.618	0.01	0.44	Retracement
2.618	0.025	0.25	Vs. Series
2.618	0.025	0.08	Retracement
2.618	0.05	0.25	Vs. Series

Scaled Chart - Duration Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
1	0	0.18	Retracement
1	0	3.19	Projection
1	0	0.90	Altern. Retracement
1.618	0	0.22	Vs. Series
2	0	0.34	Vs. Series
2	0	2.13	Retracement
2	0	4.02	Projection
2	0	1.57	Altern. Retracement
2.618	0	0.34	Vs. Series
1.618	0.01	0.22	Vs. Series
2	0.01	0.34	Vs. Series
2.618	0.01	0.34	Vs. Series
2	0.025	0.34	Vs. Series
2.618	0.025	0.34	Vs. Series
2	0.05	0.34	Vs. Series
2.618	0.05	0.34	Vs. Series

Full Info Chart - Amplitude/Price Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
1	0	3.97	Altern. Retracement
1.618	0	0.01	Vs. Series
2	0	0.36	Retracement
2	0	1.27	Projection
2	0	3.32	Altern. Retracement
2.618	0	0.34	Vs. Series
2.618	0.01	0.34	Vs. Series
2.618	0.025	0.34	Vs. Series
2.618	0.05	0.34	Vs. Series

Full Info Chart - Duration Anchoring

Ratio	Band	KDE Bootstrap Stat	Phase
0.5	0	2.54	Projection
1	0	0.20	Vs. Series
1	0	0.72	Retracement
1	0	3.92	Projection
1	0	2.91	Altern. Retracement
1.618	0	0.21	Vs. Series
2	0	0.34	Vs. Series
2	0	1.56	Retracement
2	0	5.06	Projection
2	0	2.94	Altern. Retracement
2.618	0	0.34	Vs. Series
1.618	0.01	0.21	Vs. Series
2	0.01	0.34	Vs. Series
2.618	0.01	0.34	Vs. Series
1.618	0.025	0.21	Vs. Series
2	0.025	0.34	Vs. Series
2.618	0.025	0.34	Vs. Series
1.618	0.05	0.20	Vs. Series
2	0.05	0.34	Vs. Series
2.618	0.05	0.34	Vs. Series

KDE Bootstrap Statistic: 0 = Critical Value for 95% Confidence Level

Where different phase:forecast style combinations have the same empirical densities and the KDE density is zero the test of significance has the same value

An examination of the histograms in Figure 4-8 suggests a number of further phenomena. The ratios of respondents' phases in the tabular forecasts appear to be distributed less "smoothly" than the other three. This might be suggestive of an aesthetic effect when using graphical forecasts – what might "look right" on a graph might not be chosen with only a table.

We can also assess the effect of forecast format on the distribution of ratios more formally. We pool the ratios by all modes of presentation, regardless of phase, giving four datasets. The non-parametric Kolmogorov-Smirnov (KS) test then allows us to test if two distributions are significantly different. If we turn to Table 4-6 we can see the KS p-values between survey styles. We can see that presenting respondents with more data does have a clear effect – the KS p-values of the graphical styles versus the unscaled chart style show a decrease as the respondents are provided with more information – from an unscaled chart, through providing a scale, to also providing a table of turning phases. It appears that tabular information also has an effect as per the literature. The ratio distribution from scaled charts was 12%, similar to those of the bare charts, whilst there was a 0% chance that chart-plus-table ratios came from the same distribution as the unscaled chart or scaled chart ratios. The distribution of ratios closest to chart-plus-table forecast ratios were the tabular, as opposed to any of the graphical.

Table 4-6 – Effect of across Survey Styles: KS P-Values

	Unscaled Chart	Scaled Chart	Chart-plus-Table	Tabular
Unscaled Chart	1	0.13	0.000001	0.51
Scaled Chart	0.13	1	0.0000005	0.55
Chart-plus-Table	0.000001	0.0000005	1	0.09
Tabular	0.51	0.55	0.09	1

KS-Pvalue 1 = 100% chance that phase ratios for the paired forecast styles were drawn from the same distribution

KS-Pvalue 0 = No chance that phase ratios for the paired forecast styles were drawn from the same distribution

Table 4-7 – Effect of Controlling for Respondent Characteristics: KS P-Values

Respondent Characteristic	**Control Variable 1**	**Control Variable 2**	**KS P-Value**
Culture	Chinese Respondents	Greek Respondents	0.00000000000002
Age	Respondents aged <25 years	Respondents aged >24 years	0.000001
Industry Experience	Respondents with any experience	Respondents with no experience	0.05
Gender	Males	Female	0.30
TA Knowledge	Less (<50% of survey scale)	More (>=50% of survey scale)	0.0000005
TA Opinion	Less (<50% of survey scale)	More (>=50% of survey scale)	0.01
Fundamentals Opinion	Less (<50% of survey scale)	More (>=50% of survey scale)	0.01

KS-Pvalue 1 = Respondent characteristic does not affect the phase ratios of forecasts (100% chance that phase ratios for the two control samples were drawn from the same distribution)

KS-Pvalue 0 = Respondent characteristic does affect the phase ratios of forecasts (0% chance that phase ratios for the two control samples were drawn from the same distribution)

Finally, we examined the effect of our respondents' profiles on the distribution of ratios. For each of the seven respondent characteristics we pooled the ratios into two control samples, regardless of modes of presentation or phase. We were then able to assess the effect of each characteristic by comparing each characteristic's control samples using the KS test. Significantly similar control samples would suggest that a characteristic does not influence how respondents anchor forecast phases. China and Greece were chosen to control for culture because they were the second and third most frequent countries respectively and were of a similar number. This comparison is somewhat analogous to Berlyne (1970)'s examination of Japanese and Canadian respondents. The ratios were also split between those aged under 25 and those over 24 years old to control for age. Industry experience was tested by comparing those with any experience versus those with none. TA Knowledge, TA Opinion and Fundamentals Opinion were tested by splitting the ratios between those respondents who gave higher values (>50%) versus those who gave lower values (<=50%). Gender was tested by splitting ratios between male and female respondents.

When we control for respondents' characteristics we see that all characteristics except gender had some influence on how respondents anchored phases (Table 4-7). This might be thought to support Berlyne (1970) and Thompson (1946)'s finding on culture and age respectively, but there was only weak evidence that Chinese respondents and younger respondents were anchoring more on whole numbers than Greek and older respondents. Our sample was restricted to postgraduate finance students, an appropriate sample, and this does limit the age range that we can consider.

What can we reasonably conclude from these survey results? The aim of our exercise has been to determine whether individuals have an in-built aesthetic sense of what chart retracement looks right. Had we surveyed experienced technical analysts our results would have been biased by their discipline. The fact that our sample of respondents, although not innocent of financial markets, did not consider themselves knowledgeable about technical analysts avoids this problem. Conditional on the validity of our sample, we have found some significant results, in the form of ratios that occur more frequently than might be expected to occur at random given the shape of the distribution of ratios thrown up by our survey. However, the ratios are very simple – 1 or 2. A ratio of 1 suggests a belief that prices will reverse at their most recent turning point, a standard way of calculating support or resistance levels. A ratio of 2 suggests a very simple extrapolation (doubling) of the most recent trend. None of our findings support the idea of a more complicated aesthetic involving fractional ratios like ½ or 1/8, far less Fibonacci ratios like 0.618 or 1.618. We conclude that, at least in this sample of lay individuals, there is no evidence that forecasts are anchored on Fibonacci ratios, and hence find no support for the assertion made by some technical analysts that Fibonacci retracements can represent some natural or intuitive law in financial forecasting.

4.6. APPENDICES

Appendix 4-1 – Survey Style Ratios Summaries

	Min	1st Qu.	Med	Mean	3rd Qu.	Max	SDev	Skew	Kurt
Unscaled Chart	0	0.42	0.8	1.2	1.41	39	1.69	8.31	117.51
Scaled Chart	0	0.4	0.79	1.18	1.41	19.5	1.43	4.16	26.46
Chart-plus-Table	0	0.44	0.88	1.36	1.58	29	1.87	5.68	49.25
Tabular	0.024	0.41	0.82	1.24	1.38	21.18	1.62	6.35	67.00

Appendix 4-2 – Survey Style & Specific Ratios Summaries

	Min	1st Qu.	Med	Mean	3rd Qu.	Max	SDev	Skew	Kurt
Unscaled Chart - Amplitude/Price Anchoring									
Vs. Series	0	0.31	0.55	0.60	0.83	2.68	0.38	1.32	3.54
Retracement	0	0.40	0.70	0.97	1.16	6.80	0.91	2.28	6.86
Projection	0	0.55	0.93	1.38	1.71	8.33	1.32	2.07	4.84
Altern. Retracement	0	0.55	0.93	1.78	1.50	39.00	3.68	5.50	35.74
Unscaled Chart - Duration Anchoring									
Vs. Series	0.02	0.18	0.29	0.34	0.44	1.63	0.21	1.57	3.91
Retracement	0.04	0.61	1.00	1.37	1.78	11.60	1.14	2.66	13.44
Projection	0.08	0.83	1.33	1.72	2.18	9.25	1.39	2.11	6.04
Altern. Retracement	0.07	0.71	1.10	1.45	1.72	8.22	1.22	2.42	7.57
Scaled Chart - Amplitude/Price Anchoring									
Vs. Series	0	0.29	0.50	0.58	0.80	2.55	0.39	1.30	2.93
Retracement	0	0.39	0.69	0.98	1.20	4.84	0.91	1.96	4.09
Projection	0	0.53	0.92	1.40	1.67	10.43	1.44	2.51	8.22
Altern. Retracement	0	0.52	0.96	1.27	1.42	19.50	1.66	6.03	48.17
Scaled Chart - Duration Anchoring									
Vs. Series	0.02	0.18	0.29	0.33	0.41	3.14	0.25	3.72	29.93
Retracement	0.04	0.64	1.11	1.37	1.68	12.41	1.22	3.63	22.36
Projection	0.08	0.76	1.25	1.71	2.00	10.86	1.61	2.73	9.12
Altern. Retracement	0.06	0.61	1.13	1.81	2.07	16.06	2.14	2.92	10.24
Chart-plus-Table - Amplitude/Price Anchoring									
Vs. Series	0	0.29	0.55	0.62	0.89	2.73	0.40	1.04	1.77
Retracement	0	0.42	0.74	1.02	1.30	9.38	0.95	2.66	12.62
Projection	0	0.60	1.00	1.43	1.75	16.67	1.46	3.46	22.60
Altern. Retracement	0	0.53	1.00	1.57	1.61	29.00	2.66	6.03	44.24
Chart-plus-Table – Duration Anchoring									
Vs. Series	0.01	0.22	0.32	0.38	0.46	3.73	0.27	4.11	39.68
Retracement	0.04	0.74	1.15	1.56	1.99	22.00	1.49	5.47	60.64
Projection	0.06	1.00	1.55	2.39	2.50	23.00	2.84	3.43	14.50
Altern. Retracement	0.07	0.82	1.35	1.89	2.08	23.75	2.04	4.08	27.62
Tabular - Amplitude/Price Anchoring									
Vs. Series	0.05	0.34	0.57	0.61	0.84	1.30	0.36	0.31	-0.98
Retracement	0.05	0.39	0.76	1.17	1.74	4.47	1.04	1.16	0.74
Projection	0.05	0.54	1.13	1.61	1.81	6.39	1.56	1.44	1.09
Altern. Retracement	0.05	0.60	0.92	1.70	1.32	21.18	3.34	4.82	24.38
Tabular - Duration Anchoring									
Vs. Series	0.02	0.18	0.25	0.33	0.41	1.35	0.25	1.83	4.46
Retracement	0.08	0.55	1.072	1.47	2.12	5.95	1.27	1.31	1.74
Projection	0.07	0.81	1.327	1.75	2.496	5.68	1.33	1.00	0.45
Altern. Retracement	0.24	0.66	0.99	1.27	1.42	6.60	1.10	2.84	10.22

5. FUNDAMENTALS, BEHAVIOUR AND TECHNICAL ANALYSIS WITH STRUCTURAL INSTABILITY IN EQUITIES

5.1. INTRODUCTION

This Chapter examines a number of active market-timing strategies that simulate investors' "real-time" trading decisions, through recursive forecasting of excess returns from the Standard and Poors 500 stock index. The strategies involve both technical and fundamental indicators, and our aim is to determine whether technical indicators really do add value to more conventional forecasting and trading methods.

A number of regression-based approaches to forecasting the stock market have been developed in the academic literature. Some of these use corporate sector fundamentals such as aggregate price: earnings ratios, book: market value ratios, and the spread between corporate and treasury debt yields as predictors of returns. Some models use macroeconomic indicators such as the lagged inflation rate, growth in industrial production as regressors. More recently, the behavioural finance paradigm has extended the boundaries of financial theory beyond fundamental considerations of value. This new thinking has led to trading approaches that are driven by the behavioural weaknesses of the market, and rationalises the use of price patterns such as momentum and mean reversion as possible predictors of the stock market. Finally, in parallel with these studies, technical indicators of various kinds – principally moving averages and filter rules – have been used to try to find profitable trading rules from predictions of the direction of change of the stock market.

It appears that the literature has not integrated behavioural or technical indicators into a linear regression framework. In this Chapter we therefore extend the literature by evaluating five predictor sets, comprising 1) equity fundamentals; 2) macroeconomic fundamentals; 3) behavioural variables; 4) mainstream quantative technical analysis indicators and 5) combinations of all the preceding predictors.

Most of the predictability literature implicitly assumes time-invariance in model coefficients or uses unconditional time-invariant estimation window sizes. Our models are recursively re-estimated to make "real-time" forecasts that a forecaster could have made at each point in time. We follow the methodology of the recent influential and persuasive study of stability in fundamentals-based regression models by Pesaran and Timmermann (2002). They argue that predictability is significantly improved if regression models are continuously tested for the presence of structural breaks, and that only data points in a window following the most recent structural break can be used to improve performance. Their results favoured the conditional reverse ordered cusum method (ROC) of testing for structural breaks, an adaptation of Brown, Durbin and Evans (1975)'s structural stability test.

We examine several alternative estimation window sizing approaches. We look at expanding estimation windows, which include all historical data, we look at rolling data windows of various fixed sizes, and we compare these with the Pesaran-Timmerman procedure of using data only after the most recent confirmed structural break. To extend the ROC analysis further, different structural break sensitivities and initial estimation windows are used. We also extend their analysis by accounting for transactions costs, assuming three different commission-slippage scenarios. This results in a comparison of 120 real-time recursive models with returns conditioned on the different sets of regressors, the window sizing method/parameterisation and the different transaction cost levels.

The Chapter falls into four sections. Sections 5.2 to 5.4 review stock market predictability with the fundamental based, behavioural and technical inputs. Section 5.5 introduces our data and develops a forecasting method for our recursive models. Section 5.6 discusses using the ROC approach to account for structural breaks whilst recursive forecasting. Section 5.7 reports our findings and examines some of the determinants of the different performances of the recursive models by examining predictive performance, model fit, risk-adjusted returns and returns.

5.2. FUNDAMENTALS AND PREDICTABILITY

Various fundamentals have been proposed as means to identifying profitable opportunities, with much of the predictability of stock returns coming from valuation ratios and interest rates. Vuolteenaho (2002) and Cohen et al (2002) show the role of book-to-market values in explaining future earnings and profits, a phenomenon that feeds into equity returns. Campbell & Shiller (1987) show that firm PE ratios predict subsequent returns over the following ten year period. Other studies that support this idea include Fama and French (1992), Fuller et al (1993), Jaffe et al (1989) and Roll (1994). The Fama and French (1992) three factor model itself makes use of the book-to-market value, one of three primary value measures alongside PE ratios and dividend yields. These predictors have also been used to forecast the aggregate stock market, the subject of our study. Lander et al (1997) use PE and bond yields regressions to forecast the Standard and Poors 500. Pesaran and Timmerman (2002) model equities in a recursive framework using the dividend yield, T-bill rates and the default premium on corporate bonds.

Macroeconomic variables that exhibit clear business cycle variations, such as inflation, industrial production, money supply and oil prices have also been used to predict the stock market (Pesaran and Timmerman, 1995 and Pesaran and Timmerman, 2000). These variables represent undiversifiable risk factors that effect economic agents both directly and via interest rates. Inflation and money supply growth negatively affect the level of returns (Bodie, 1976, Fama, 1981, Geske and Roll, 1983, and Pearce and Roley, 1983 and 1985). However, the relationship of returns with real sector economic measures has been notoriously difficult to establish (Chen, Roll and Ross, 1986), though there is evidence that measures such as GDP, industrial production or employment do influence the volatility of returns (Flannery and Protopapadakis, 2002).

5.3. BEHAVIOURIAL PHENOMONA AND PREDICTABILITY

We could view this fundamentals-based predictability as reflecting a set of systematically varying rational risk-premia (see Fama and French, 1992). We could alternatively see this as a behavioural phenomenon driven by over (under) reactions to information. Shiller (2002) highlights the excess volatility of real stock prices relative to its discounted present value, and the influence of mass psychology around efficient pricing of equities. Daniel et al (1998) explain this in terms of investor overconfidence whilst Hong and Stein (1999) suggest investors add volatility by initially under-reacting, and follow this with later overreaction.

Correlations in returns over the intermediate and long term have been found that are not explained by fundamental factors. De Bondt and Thaler (1985) found that returns over three to five year periods are negatively correlated, creating long term reversals in prices. They also found positive correlation in the returns of one year winners, which outperformed one year losers (see also Barberis and Thaler, 2002). This momentum phenomenon was first tested extensively by Jegadeesh and Titman (1993), showing that stocks that performed exceptionally well beat the losers over the following year.

The long term reversal phenomenon can be partially explained by the three factor model (Fama and French, 1996), but momentum in 3 to 12 month returns cannot, and therefore remains outside a risk-premia framework, arguably due to limits on arbitrage (Korajczyk and Sadka, 2004). When controlling for macroeconomic factors both momentum and long term reversals are robust (Cooper et al, 2004). Grundy and Martin (2001) further find that whilst factor models can explain much of the variability of momentum returns, they do not explain their mean returns (see also Jegadeesh and Titman, 2001).

5.4. TECHNICAL ANALYSIS AND PREDICTABILITY

The remaining branches of the predictability literature tend to be grouped under the title of "trading rules", encompassing a range of mechanical price driven techniques from elements of textbook technical analysis through to more general machine learning approaches. Park and Irwin (2004) provide a comprehensive review of these studies. Of 92 studies published in the period 1988-2004, 58 reported positive excess profits from a technical rule, 10 yielded mixed results, and 24 reported losses. Even allowing for a bias towards publishing positive results, and the possibility that not all studies properly accounted for transactions costs and risk, this does suggest that not all of technical analysis can be dismissed prima facie.

Early studies examined "filter rules", which trigger trades when prices rise or fall in excess of a defined percentage. Whilst Alexander (1961), Fama and Blume (1966) and Sweeney (1988) found no value in such rules in the equity markets, Sweeney (1986) and Levich and Thomas (1993) successfully implemented a number of different sized filters on daily closing prices of major currencies. Using a bootstrap approach, Brock *et al* (1992) found statistically significant forecasting ability in the Dow Jones Industrial Average using a channel-breakout system, generating trades on breaks of resistance or support, and using moving averages. Their level breakout results potentially stem from the order-flow price cascade thesis of Osler (2001 and 2002), but methodological weaknesses do exist in their study. Transaction costs are not accounted for. Data-snooping problems were revealed by Sullivan *et al* (1999). Their re-examination of Brock *et al* (1992) used a bootstrap methodology to correct for the effects of data-snooping in a way that was not previously possible. A universe of approximately eight thousand parameterisations of trading rules gave similar results to Brock *et al* (1992), but failed a ten year out-of-sample test. Nevertheless, a key point of Brock *et al* (1992) still stands. The returns resulting from its strategies were not consistent with either a random walk in the stock index, an AR(1) process, or processes overlaid with GARCH-M or Exponential GARCH models for residual volatility.

Neural network systems driven by moving averages have also generated profits in some stock market applications (Gencay 1996 and 1998), yet the moving average application in the forex markets have not found profitability (Lee and Mathur, 1994, Lee, Gleason and Mathur, 2001, Lee, Pau and Liu, 2001 and Olson, 2003). Allen and Karjalainen (1998) used genetic algorithms to generate a trading system that switched between stocks and T-bills between 1928 and 1995. Consistent excess out of sample returns were not achieved, with Neely et al. (1997) reaching a similar conclusion. Neely et al (1997) also used a genetic programming approach to identify trading rules across a variety of currencies in the period between 1975 and 1980 and then scrutinized their out of sample performance between 1981 and 1995. Neely and Weller (1999) found that the profitability of single trading rules are consistently lower than the profits from the more complex genetic combination of a number of indicators.

5.5. DATA AND EXPERIMENT DESIGN

The basis of our method is an active market-timing strategy that simulates investors' "real-time" forecasts as trading decisions through recursive forecasting of the US stock market. The fundamental data, technical indicators and statistical techniques were all available during the sample period. Treasury Bill rates, industrial output, M0 money supply and Moody's Aaa and Baa corporate bond yield indices are sourced from Datastream. The remaining fundamental data is from the Shiller (2001) dataset kindly made available on Shiller's website. The dataset run from February 1971 until September 2003. Fundamental variables and macro-economic variables are lagged one and two periods respectively.

The recursively estimated models forecast out-of-sample excess returns at $t+1$, only using data available at t. Excess returns are defined as monthly total returns from holding the Standard and Poors 500 index minus monthly T-bill returns. Where excess returns are forecast as positive, the S&P500 is held for capital gain and dividend income. Where negative excess returns are forecasted, T-bills are held. We estimate returns based on real-time forecasts from recursive models conditioned on a number of factors that we test for sensitivity: different sets of regressors, the real time window sizing method, the initial window size and different commissions levels. This results in 120 real-time recursive models.

Five different sets of regressors are employed in the least squares regressions. A base set, three sets of regressors consisting of this base set plus additional variables, and a set containing all nonduplicated variables from all sets:

1) Base regressors

Constant, Dividend Yield(t-1), the one month deannualised Tbill rate(t-1), the Default Premium(t-1), defined as the yield spread of Moody Baa rated bonds over Aaa rated bonds, and CPI(t-2)

2) Base plus fundamentals

Dividends(t-1), earnings(t-1), PE Ratio(t-1), 10 year average PE Ratio(t-1) (as per Shiller, 2001), log change in industrial production(t-2), log change in M0 money supply(t-2)

3) Base plus behaviourals

3 month, 12 month and 36 month log-returns to capture momentum and long run reversals

4) Base plus technicals

A representative selection of nonlinear technical indicators detailed below (12 month highs and lows, moving averages versus price, moving averages versus other moving averages, DI, ADX and RSI)

5) Base plus all variables

The fifth set of regressors uses all unique variables from the initial four sets

The technical indicators used were selected because of their mainstream usage amongst practitioners (Murphy, 2000). The 'base plus technicals' inputs contain:

a) the support & resistance levels from the 12 month highs and lows in the index,

b) the ratios of the index to its 6, 12 and 36 month moving averages,

c) the ratios of 6, 12 and 36 month moving averages to moving averages with twice the sample size,

d) the 6, 12 and 36 month Directional Index (DI),

e) the 6, 12 and 36 month Average Directional Index (ADX) and

f) the 6, 12 and 36 month Relative Strength Index (RSI).

The calculation the support and resistance levels and the moving averages indicators are self-explanatory. The DI, ADX, and RSI indicators are calculated as follows. The DI (Wilder, 1978) is a momentum indicator that quantifies directional behaviour of a market, attempting to identify stronger trends in that the hope that they persist. It is based on the largest part of the current period's price range that is outside the previous period's price range. Where the greater excess is above (below) the previous period's high (low), this is regarded as positive (negative) Directional Movement, +DM (–DM) – a day is either allocated a +DM *or* a –DM value. Where there are inside or outside bars (bars that are enveloped by or envelope the previous bar) an inside day's +DM and –DM will always equal zero and where there are outside days the larger of the positive +DM and –DM is used. The positive (negative) Directional Indicator, +DI (–DI), is the exponential moving average (EMA) of the +DM (-DM) divided by the Average True Range (ATR), a measure of volatility defined by Wilder (1978). This can be formally expressed as:

$$+DM_{t_0} = H_{t_0} - H_{t_{-1}} \qquad +DI_{t_0} = \frac{EMA^{n}_{t_0}(+DM)}{ATR^{n}_{t_0}}$$

$$-DM_{t_0} = L_{t_{-1}} - L_{t_0} \qquad -DI_{t_0} = \frac{EMA^{n}_{t_0}(-DM)}{ATR^{n}_{t_0}}$$

The ATR is the EMA of True Range (TR). True Range is defined by Wilder as the largest of the following: the difference between H_{t0} and L_{t0} (the high and low of the current period respectively), the difference between C_{t-1} and H_{t0} or the difference between C_{t-1} and L_{t0}. This multifaceted definition of volatility stems from Wilder's attempt to account for gaps (prices at which no trading took place) between periods when calculating range:

$$TR_{t_0} = \max\begin{cases} abs(H_{t_0} - L_{t_0}) \\ abs(H_{t_0} - C_{t_{-1}}) \\ abs(C_{t_{-1}} - L_{t_0}) \end{cases} \quad ATR^n_{t_0} = EMA^n_{t_0}(TR)$$

Wilder (1978) developed the ADX from the +/–DI to quantify the extent to which a security is trending. ADX is calculated by taking the absolute value of the difference between $+DI_{t0}^n$ and $-DI_{t0}^n$ and dividing this by the sum of $+DI_{t0}^n$ and $-DI_{t0}^n$ to obtain the Directional Index (DX). ADX is then obtained by calculating the EMA of DX for n periods:

$$DX_{t_0} = \frac{abs((+DI^n_{t0}) - (-DI^n_{t0}))}{(+DI^n_{t0}) + (-DI^n_{t0})}$$

$$ADX^n_{t_0} = EMA^n_{t_0}(DX)$$

Wilder (1978)'s RSI is an extremely popular momentum oscillator amongst practitioners. RSI compares the scale of a security's recent gains to the scale of a security's recent losses and standardises that information between 0 and 100. Although the term "relative strength" is used, it has no relation to intermarket analysis of the ratio between a two securities or indices. RSI calculation is performed in several stages: the differences between the closing prices are averaged separately for where changes are positive or negative for n periods. This results in an average upward and downward price changes within the specified sample.

$$Upchange_{t_i} = \begin{cases} (C_{t_i} - C_{t_{i-1}}) \text{ if } (C_{t_i} - C_{t_{i-1}}) > 1 \\ \text{else } 0 \end{cases}$$

$$Downchange_{t_i} = \begin{cases} (C_{t_i} - C_{t_{i-1}}) \text{ if } (C_{t_i} - C_{t_{i-1}}) < 1 \\ \text{else } 0 \end{cases}$$

$$\text{Average Up Change}^n_{t_0} = EMA^n_{t_0}(Upchange_{t_i})$$

$$\text{Average Down Change}^n_{t_0} = EMA^n_{t_0}(Downchange_{t_i})$$

The "relative strength" (RS), in terms of RSI, is computed by dividing the average upward change by the average downward change and standardised between 0 and 100:

$$RS^n_{t_0} = \frac{\text{Average Up Change}^n_{t_0}}{\text{Average Down Change}^n_{t_0}}$$

$$RSI^n_{t_0} = 100 - \frac{100}{1 + RS^n_{t_0}}$$

Three transaction cost scenarios are used. These are based on commission and slippage assumptions from Pesaran and Timmerman (1995): a no commission scenario, a low commission scenario (0.5% equities, 0.1% Tbills) and a high commission scenario (1% equities, 0.1% Tbills).

5.6. STRUCTURAL STABILITY AND THE REVERSE ORDERED CUSUM

The size of the real-time estimation window is determined in three different ways: a window starting after the most recent structural break, a rolling window and an expanding window comprising of all data from the start of the series. We can therefore compare a window size conditioned on the last break to using both a fixed window size and a window that includes all data prior to the forecast point.

To test for the most recent structural break we implement a reverse ordered cusum squared (ROC) break dating technique as a recursive structural stability test. This is an implementation of Brown et al (1975)'s test by Pesaran and Timmermann (2002).

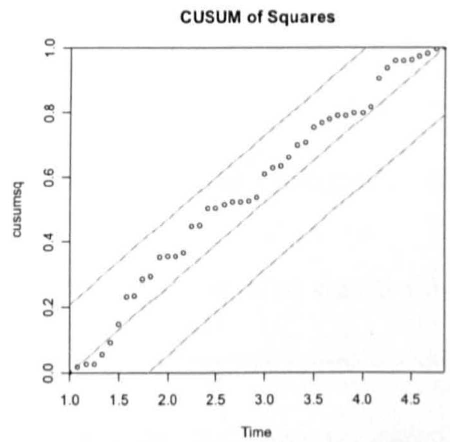
The ROC approach applies Brown et al (1975)'s cusum squared tests to observations reversed in time to identify the most recent break. Pesaran and Timmermann compared a number of approaches to dealing with structural instability when estimating their recursively estimated trading system. They found that the ROC approach best increased predictive performance versus the other unconditional and conditional methods. As we shall see, predictive performance is central to the needs of a trading system and is more important to profitability than model fit.

Dating of the most recent ROC break point is estimated as follows. Prior to the trade-decision forecast of t_{n+1} at t_n the recursive residuals are calculated and reverse ordered. This is a separate recursive process from the recursive trading decision forecasting. The reversed recursive residuals are the residuals of forecasts of t_n, t_{n-1}, $t_{n-2} \ldots t_{0+X}$ where X is the initial estimation window length. $X = 120$ months is tested in addition to $X = 60$ months, which Pesaran and Timmerman used. These forecasts are made using only data in-sample to that estimation, starting at t_0 and at ending at t_{n-1}, t_{n-2}, $t_{n-3} \ldots t_{0+X-1}$. The reversed recursive residuals are then squared and cumulated to give the cumulative sum of recursive residuals – hence reverse ordered cusum squared. Pesaran and Timmerman reconfirmed prior findings that the CUSUM squared method detects breaks better than the standard (unsquared) cusum. The squared recursive residuals are reversed prior to being cumulatively summed because cusum methods identify the first break point in a series from t_0. We require the most recent break in the series, and our post-break estimation window must run until the most recent data point at t_n. The cusum squared series is then standardised and critical values are taken from Brown et al (1975) to determine the break point.

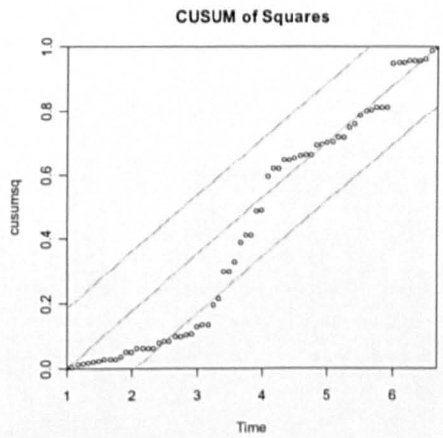
Forecasting whilst accounting for structural breaks is a two stage process. Firstly, investors must monitor and test for breaks in 'real-time' – before every the forecast the ROC test must estimate the most recent break. Secondly, they must use an estimation window based on the post-break data to generate the forecast. This two stage process must of course be executed for each recursive forecast to replicate real-time break monitoring and forecasting. For every forecast ROC identifies the date of the most recent break and thus the sequence of post-break estimation windows that an investor could identify in real-time. As per the suggestion in Pesaran and Timmermann (2002), we assume a minimum break window of twice the number of regressors. Whilst Pesaran and Timmermann made use of only one ROC p-value not documented in their paper, we test our models using ROC p-values of both 2.5% and 10% that a break has occurred. This allowed us to estimate recursive models with lesser and greater sensitivity to breaks respectively.

It is useful to understand how the reversed CUSUM squared line evolves graphically. Figure 5-1 plots the reversed CUSUM squared from an example model at four points in time. The data points on the left are from the most recent recursive residuals, as the reversing means that new recursive residuals are "introduced" at the start of series. The data points on the right are from the earlier recursive residuals. In graphic A the line is entirely contained by the confidence intervals and thus no breaks are detected. The entire dataset would then be used to estimate the model. As time moves on our forecaster has roughly double the amount of historical data available (graphic B). A break would be detected "early" in the series, at the point where the CUSUM squared line moves below the critical band. Note that because the recursive residuals were first reversed this is a relatively recent break. Our estimation window size is therefore the number of data points from the start of the series until the first break of the confidence intervals. By graphic C we can see that the same break point has moved along the series and is still being detected. That break point is of course now older than before and thus the window size is larger. Once the forecaster has all the data in graphic D, no breaks are detected. The average recursive residuals that transpired since C were sufficiently small to reduce the volatility of the reverse CUSUM squared line versus its mean. The entire dataset is then used again for model estimation.

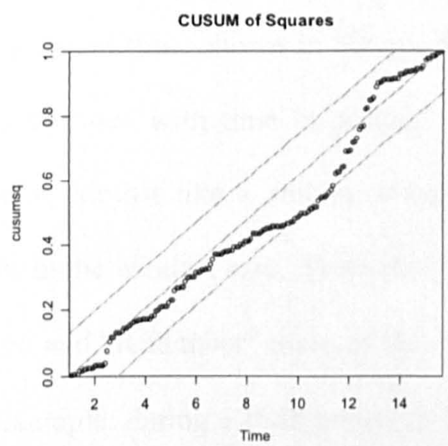
Figure 5-1 – Example Evolution CUSUM of Squares



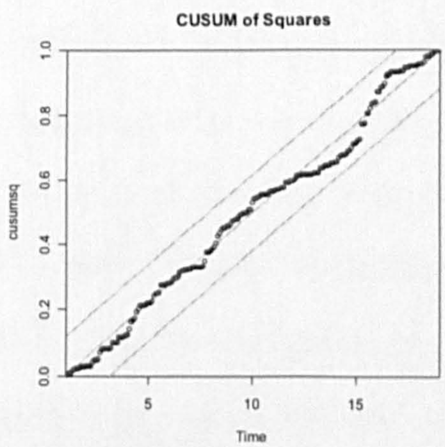
A



B



C



D

For each regressor set and model, the initial window size X for estimating the first break is tested with values of both 60 and 120 months. The initial window size for break detection also determines the tested rolling window sizes and initial expanding window sizes. Pesaran and Timmermann (2002) considered only one rolling window period of 60 months. These different window sizing methods and parameterisations provide context for our examination of the ROC approach.

5.7. OUT OF SAMPLE RESULTS

Figure 5-2 gives a three page example of the output from one of the 120 estimated recursive models. This model set uses all predictor variables, is less sensitive to breaks, and the window required for the initial break estimation is 60 months.

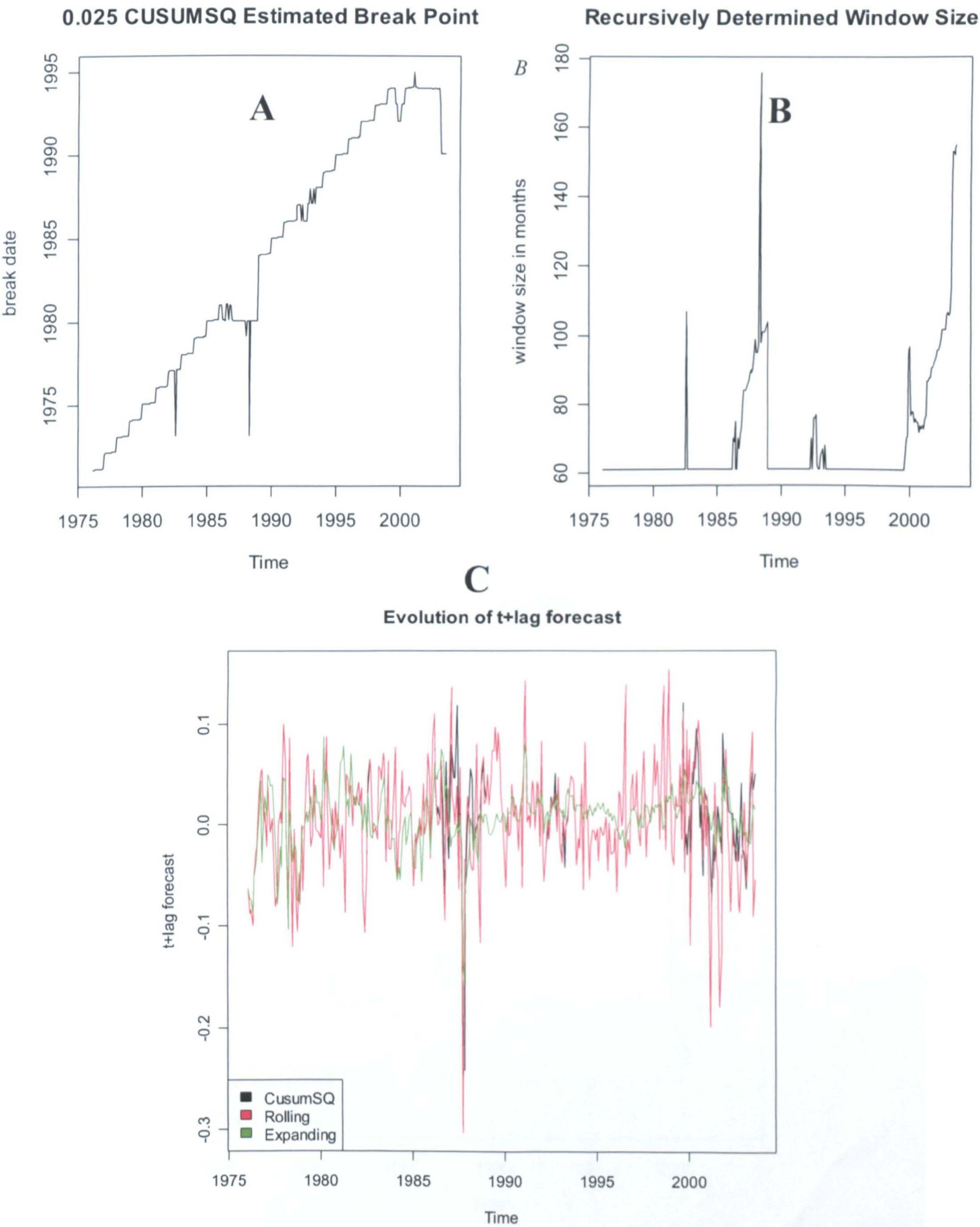
In graph A we can see what would have been the most recent ROC break date at every data point, excluding the initial window. In this example we can see that the break date tends to move with time for most of the SP500 history.

This break date can then be used to calculate the number of data points to be used at each point in time, shown in the graphic B. We can see that because the break date tends to move with time in graphic A, the window size in graphic B is generally constant, almost like a rolling window. Yet there are occasional and substantial spikes in the window size. From this we can see that the model sometimes decided to rely on and "remember" more of the past. This occurred at some critical junctures in this example: during a short period in 1982, the mid-1980s around the 1987 crash, the 1992 recession and the bursting of the 1990s equity bubble.

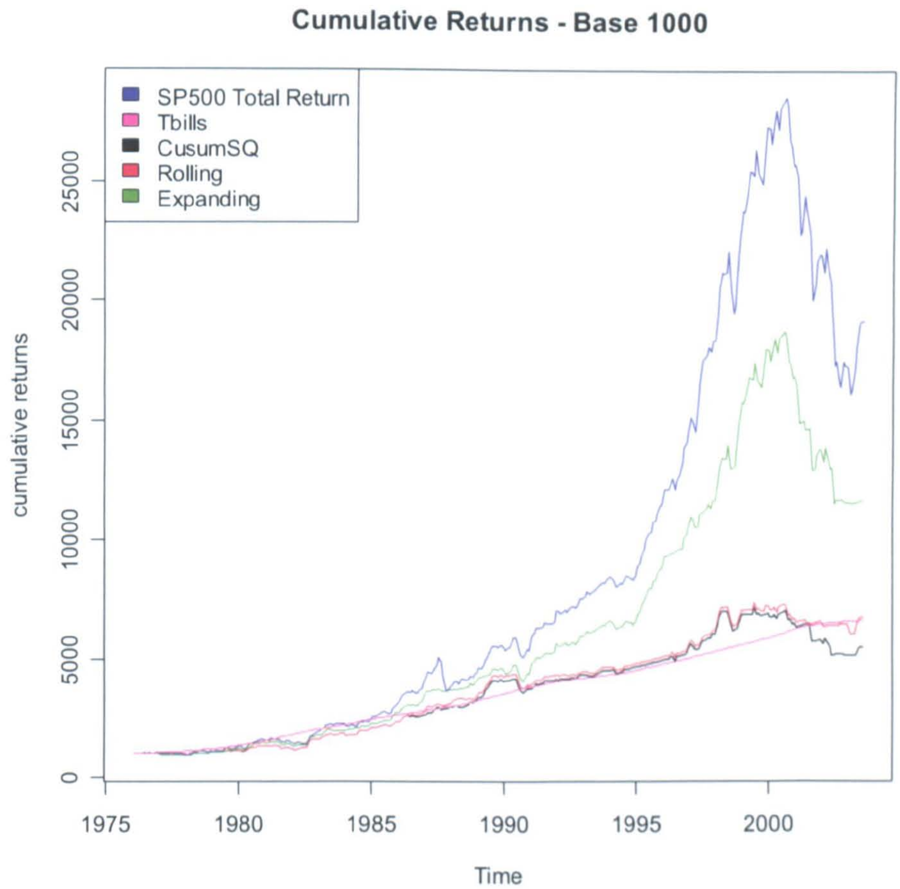
Graphic C in Figure 5-2 shows the forecasts of excess returns under the three window sizing methods: the rolling window size, initial expanding window size and size of the initial window for estimating the most recent break are all 60 months. The forecasts therefore all commence at the same point in time. Allowing the model to use all pre-forecast data means that, for better or for worse, the expanding window forecasts are not hostage to any idiosyncratic characteristics of a smaller sample. As we would expect, expanding window forecasts are therefore relatively stable.

The cumulative returns are in graphic D. Positive forecast excess returns mean that equities are held for total return and negative forecasts dictate that T-bills are held. We can see that the expanding window is more correlated to the index because of its use of all available data. The rolling and ROC (marked CusumSQ) window methods generated T-bill returns with more risk and are also closely correlated in this specific example. This is because of the 31 regressors in the "Base plus All" regressor set. The minimum window size of double the number of regressors therefore excludes the possibility of window sizes of less then 62 data points – and the rolling window size is 60.

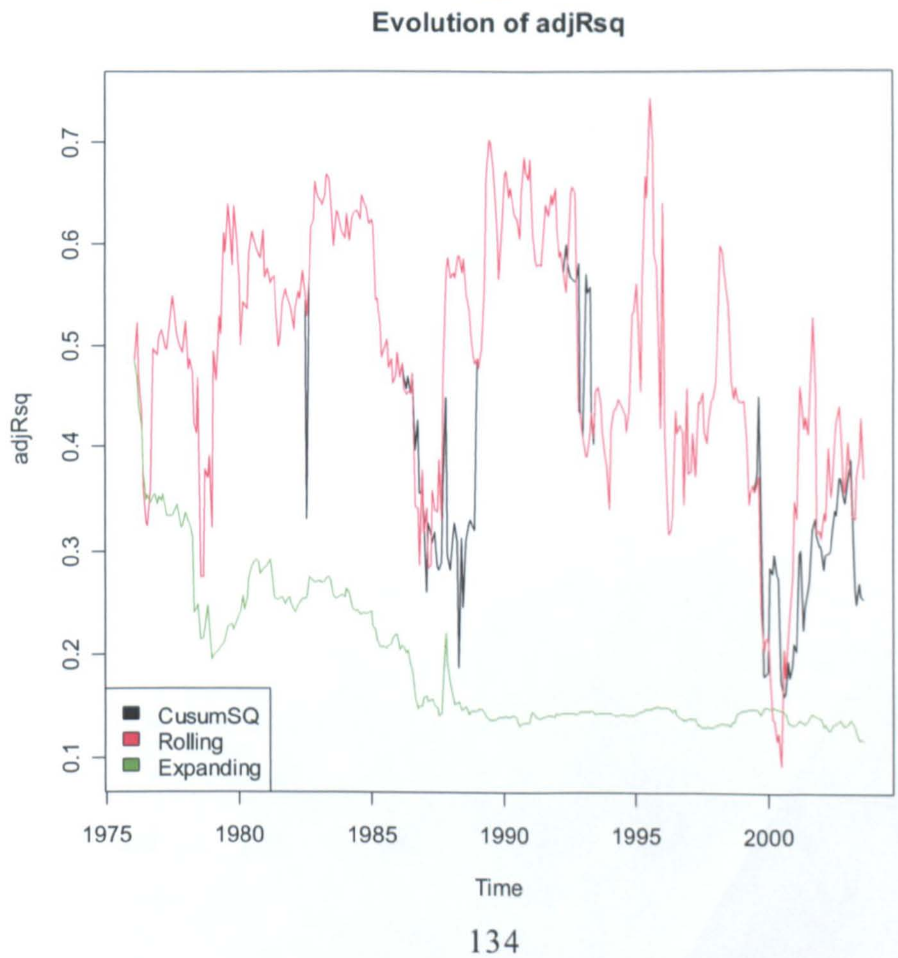
Figure 5-2 – 'Base plus all' regressor set, ROC p-val 0.025, initial.window 60



D


Cumulative Returns - Base 1000
SP500 Total Return
Tbills
CusumSQ
Rolling
Expanding
cumulative returns
0
5000
10000
15000
20000
25000
1975
1980
1985
1990
1995
2000
Time

E


Evolution of adjRsq
CusumSQ
Rolling
Expanding
adjRsq
0.1
0.2
0.3
0.4
0.5
0.6
0.7
1975
1980
1985
1990
1995
2000
Time

F


Evolution of Sharpe Ratio after t12
Sharpe Ratio
Time
CusumSQ
Rolling
Expanding
1975
1980
1985
1990
1995
2000
-4
-2
0
2
4
6

G


Evolution of Market Timing Stat after t12
Market Timing Stat
Time
CusumSQ
Rolling
Expanding
1975
1980
1985
1990
1995
2000
-0.3
-0.2
-0.1
0.0

In graphic E we can see the evolution of model fit for three methods. As we would again expect, the expanding window fit is more stable than allowing the model to exclude data. The model fit of the rolling and ROC windows are however consistently and substantially higher. Model fit is therefore not of clear value when seeking to understand the relative over performance of the expanding window. It is by other measures that the expanding window's merit in this example can be seen. The risk adjusted returns in graphic F and predictive performance of graphic G show the superior performance of the expanding window, despite the lower average adjusted R^2 shown by graphic E.

Each of the 120 recursive models generates series that record monthly model performance exactly as would be calculated in real-time by an investor trading on the model. This allows us to evaluate the evolution of performance over time. From these histories of model performance we can calculate average historic performance of a model and see how stably the different performance measures evolved over the sample. Such metrics are of importance. Take the Sharpe ratio for example, the ratio between return and its standard deviation and our measure of risk adjusted return. An investor may change his mind about trading a model with a Sharpe ratio of 2 if the ratio has a month-to-month volatility of 1 and instead opt for a model with a more stable Sharpe ratio.

Appendix 5-1 and Appendix 5-2 list the results of all 120 recursive models. They are split by initial/rolling window size because the tradable period differs. Whilst the same length of dataset is used by all parameterisations of the models, the use of a larger initial/rolling window does reduce the tradable period. By using more of the initial data for model estimation and hence being able to enter any positions later, benchmark returns and cumulative returns are lower.

The following performance statistics are given for each forecasting combination in Appendix 5-1 and Appendix 5-2:

- The proportion of correctly predicted forecast signs
- The Pesaran & Timmermann (1992) market timing statistic
- The average adjusted-R^2 for the models estimated *within* each real-time recursive model
- The Sharpe ratio
- The cumulative return.

The tables also provide the window sizing method for each model, the break p-values for the ROC based models, the regressor set used and the level of commissions. We can see that a number of real-time recursive models do outperform the Standard and Poors 500 total return benchmark, both in returns and on a risk-adjusted basis. The technical regressor set, the ROC method and the rolling window perform relatively well in risk adjusted returns. Conditioning the estimation window on the last break using ROC also benefits the model fit. So that we can quantify the sensitivity of performance, the following tables summarise these results conditioning on each factor. These summaries aggregate the models by these factors to give us average performance *across* real-time recursive models and the volatility of that performance.

When summarising performance *across* real-time recursive models by the initial/rolling window (Table 5-1) it appears that no window method or regressor set consistently generated models with returns that outperform the Standard and Poors 500 total return benchmark. It is also clear from Table 5-1 that model fit need not lead to superior returns or risk-adjusted performance. This phenomenon is again shown clearly in Table 5-2, which breaks down the real-time recursive model performances by all five regressor sets.

Table 5-1 – Results controlling for initial estimation/rolling window size

When t.initial = 60

Benchmarks

	Sharpe Ratio	Return
S&P Total Return	1.88	1812%
Tbills	40.38	562%

Model performance by window method

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	57%	6%	0.0171	0.0325	27%	13%	1.91	0.90	817%	802%
Expanding Window	59%	3%	0.0167	0.0202	13%	3%	1.49	0.86	744%	742%
Rolling Window	55%	6%	0.0257	0.0422	27%	15%	1.98	0.66	737%	743%

Model performance by independent variable set

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	60%	1%	0.0115	0.0213	12%	1%	1.29	0.76	767%	802%
BaseplusAll	49%	3%	-0.0283	0.0133	41%	13%	1.57	0.70	324%	291%
BaseplusBF	61%	1%	0.0435	0.0196	15%	3%	1.82	0.86	857%	804%
BaseplusFunda	61%	2%	0.0468	0.0116	21%	5%	1.85	0.65	1076%	955%
BaseplusTA	54%	4%	0.0220	0.0221	29%	10%	2.57	0.79	870%	694%

When t.initial = 120

Benchmarks

	Sharpe Ratio	Return
S&P Total Return	2.01	1122%
Tbills	51.98	325%

Model performance by window method

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	59%	6%	0.0149	0.0294	25%	13%	1.96	1.00	489%	456%
Expanding Window	61%	4%	0.0041	0.0133	12%	3%	1.52	1.03	469%	456%
Rolling Window	59%	4%	0.0218	0.0151	16%	8%	1.99	0.85	516%	461%

Model performance by independent variable set

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	62%	2%	0.0114	0.0195	11%	1%	1.37	0.86	637%	673%
BaseplusAll	50%	4%	-0.0241	0.0150	38%	13%	1.57	0.69	302%	269%
BaseplusBF	62%	2%	0.0379	0.0192	13%	3%	1.76	0.90	684%	673%
BaseplusFunda	62%	2%	0.0377	0.0159	19%	5%	1.80	0.73	835%	800%
BaseplusTA	55%	3%	0.0197	0.0158	25%	10%	2.69	0.82	716%	572%

Table 5-2 – Results controlling for Regressor Set

Base

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio
ROC Window	62%	2%	0.0067	0.0069	12%	1%	1.32	0.90
Expanding Window	60%	1%	-0.0090	0.0029	11%	1%	1.11	0.80
Rolling Window	61%	1%	0.0412	0.0039	10%	2%	1.73	0.84

BaseplusAll

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio
ROC Window	48%	1%	-0.0361	0.0019	47%	1%	1.48	0.66
Expanding Window	55%	1%	-0.0086	0.0021	18%	1%	1.33	0.62
Rolling Window	51%	4%	-0.0155	0.0172	39%	11%	1.98	0.73

BaseplusBF

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio
ROC Window	62%	1%	0.0397	0.0171	16%	2%	1.96	0.94
Expanding Window	63%	2%	0.0196	0.0042	10%	0%	1.18	0.73
Rolling Window	61%	1%	0.0527	0.0193	12%	3%	1.94	0.81

BaseplusFunda

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio
ROC Window	62%	2%	0.0428	0.0103	23%	2%	1.96	0.62
Expanding Window	63%	1%	0.0224	0.0156	13%	1%	1.28	0.79
Rolling Window	61%	2%	0.0428	0.0179	19%	4%	2.00	0.75

BaseplusTA

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio
ROC Window	55%	0%	0.0269	0.0067	31%	4%	2.94	0.72
Expanding Window	58%	0%	0.0275	0.0097	12%	1%	2.63	0.96
Rolling Window	51%	3%	-0.0025	0.0131	26%	12%	2.27	0.79

For example, the 'base plus fundamentals' regressor set has the highest returns in each scenario, holds second place by Sharpe ratio and yet this is driven by a mediocre adjusted-R^2. For both values of initial/rolling windows the 'base plus technicals' variables generated risk-adjusted returns over those of the benchmark and all other predictor variables. This is despite being consistently surpassed by the 'base plus all' predictors in adjusted-R^2; the combination of fundamental, behavioural and technical variables best encapsulates the dynamics of month to month excess returns. Moreover, despite the leading superior model fit of the 'base plus all' set, it has the second lowest Sharpe ratios for both initial/rolling windows. The correlation matrix of prediction performance, model fit, risk adjusted return and return shows the confused relationship between different measures of performance (Table 5-3).

Table 5-3 – Correlations between different performance measures

	Sign Test	Market Timing Stat	Avg AdjRsq	Sharpe Ratio	Return
Sign Test	1.00				
Market Timing Stat	0.74	1.00			
Avg AdjRsq	-0.87	-0.58	1.00		
Sharpe Ratio	-0.11	0.26	0.14	1.00	
Return	0.25	0.31	-0.19	0.07	1.00

What we see is that a higher in-sample model fit leads to lower out-of-sample predictive performance, as measured by the sign test and the market timing stat. This example of classic over-fitting is also reflecting in the relationship between model fit and return. Other than this trade-off, the market timing statistic offers little discernable pattern other than leading to selection of the 'base plus behaviourals' and 'base plus fundamentals' regressor sets (Table 5-1 and Table 5-2) – these regressor sets hold the second and third places in Sharpe ratio performance with Sharpe stability comparable to the other regressor sets.

The expanding window is noticeably more stable in model fit (Table 5-1), as might be expected, yet it generates half the adjusted-R^2 of the ROC window method for both initial window values and decisively has the lowest Sharpe ratio. Whilst the rolling windows generated the highest Sharpe ratios, these were only marginally higher than the ROC break based windows. Furthermore, increasing the initial/rolling estimation window from 60 to 120 months almost halves the adjusted-R^2 of the rolling window method. This is perhaps unsurprising a priori – a rolling window is arbitrary whilst ROC or expanding windows adapt to data evolution, albeit in a different manner. This arbitrariness versus adaptability point can be seen in the lack of change in ROC or expanding window adjusted-R^2 when increasing the initial window. When examining the results by regressor set (Table 5-2), both ROC and rolling windows again outperform the expanding windows. Yet it is perhaps this arbitrariness of a rolling window that drives the instability in its relative instability in adjusted-R^2, but this is once again not consistently reflecting in Sharpe variability.

Table 5-2 shows that the highest Sharpe ratios were attained using 'base plus technicals' variables with ROC estimation windows. The poor performance of the expanding window and the arbitrary nature of rolling windows prompts further examination of the ROC windows. We have already seen the relative insensitivity of ROC break dating to the initial window size and Table 5-4 shows ROC sensitivity to break p-values (more data is available in Appendix 5-3). Allowing for detection of less significant breaks with a p-value of 10% consistently generated higher adjusted-R^2 values and Sharpe ratios and generally higher returns, versus using a p-value of 2.5%. The variability of the Sharpe ratio was also marginally lower with a p-value of 10% (Appendix 5-3). The regressor sets that benefited the least from the increased sensitivity from a 10% p-value were the 'base plus fundamentals' and 'base plus technicals" sets. The 'base' regressor set's mild improvement in model fit is contrasted with it benefiting the most in market timing predictive power, risk adjusted returns and cumulative returns.

Table 5-4 – Improvement from 10% ROC p-values versus 2.5% p-values

	Market Timing Stat	**AdjRsq**	**Sharpe Ratio**	**Return**
Base	1060%	9%	42%	25%
BaseplusAll	-5%	2%	12%	15%
BaseplusBF	132%	10%	35%	18%
BaseplusFunda	-36%	16%	5%	-3%
BaseplusTA	-1%	26%	3%	-8%

Different commission scenarios are implemented in Table 5-5 to show the resilience of the different strategies to different commission levels. Returns are unsurprisingly slashed at all levels of commission. The primary point to note is that the only predictor set that maintained a respectable Sharpe ratio was the 'base plus technicals' regressor set.

Table 5-5 – Results controlling for Commissions

No Commissions

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	2.77	0.61	1374%	663%
Expanding Window	2.32	0.72	1374%	439%
Rolling Window	2.76	0.37	1302%	615%

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	2.25	0.43	1497%	384%
BaseplusAll	2.31	0.33	602%	250%
BaseplusBF	2.63	0.48	1529%	422%
BaseplusFunda	2.52	0.30	1804%	584%
BaseplusTA	3.56	0.42	1347%	517%

Low Commissions

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	2.01	0.59	454%	236%
Expanding Window	1.60	0.59	378%	117%
Rolling Window	2.05	0.31	444%	184%

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	1.48	0.34	370%	100%
BaseplusAll	1.60	0.27	232%	71%
BaseplusBF	1.87	0.46	436%	129%
BaseplusFunda	1.90	0.31	559%	213%
BaseplusTA	2.73	0.34	566%	225%

High Commissions

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	1.02	0.66	132%	120%
Expanding Window	0.60	0.53	68%	57%
Rolling Window	1.14	0.35	134%	67%

Commission effect by window method

	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	0.38	0.31	45%	42%
BaseplusAll	0.80	0.24	72%	23%
BaseplusBF	0.78	0.47	89%	62%
BaseplusFunda	0.98	0.46	143%	92%
BaseplusTA	1.79	0.33	235%	116%

This study leads us to several conclusions. First, we can see that using the criteria of predictive performance, model fit, risk-adjusted returns or returns can lead to different model selection choices. Second, the models that include technical indicators provided the only respectable risk-adjusted returns after introducing commissions and also generated returns that were less affected by costs. Testing for structural instability via the ROC method does lead to improved performance by every measure when compared to an expanding window. This observation is strengthened when the estimation window is more sensitive to potential breaks, thus moving further from an expanding window's assumption of using all previous data. Third, there are models where the rolling window outperforms ROC windows, yet this stems from choices of window sizes that are not conditioned on the data. If we see interruptions in structure that exceed the length of the rolling window, the model has no "memory" of estimations that may need to be reverted back to. Arbitrary data exclusion could arguably be worse than the unconditional inclusion of data by an expanding window.

Appendix 5-1 – All results, Initial/Rolling Window 60 months

	ROC Pval	Independent Variables	Commission Profile	Sample Start	Sample End	Lag	Initial / Rolling Window	Correct Signs	Market Timing Stat	Avg AdjRsq	Sharpe Ratio	Return
S&P Total Return				1971.02	2003.09		60				1.88	1812%
Tbills				1971.02	2003.09		60				40.38	562%
ROC Window	2.5%	Base	High Commissions	1971.02	2003.09	-1	60	60%	-0.0037	12%	0.14	16%
ROC Window	2.5%	Base	Low Commissions	1971.02	2003.09	-1	60	60%	-0.0037	12%	1.17	335%
ROC Window	2.5%	Base	No Commissions	1971.02	2003.09	-1	60	60%	-0.0037	12%	1.86	1582%
ROC Window	2.5%	BaseplusAll	High Commissions	1971.02	2003.09	-1	60	47%	-0.0385	47%	0.64	55%
ROC Window	2.5%	BaseplusAll	Low Commissions	1971.02	2003.09	-1	60	47%	-0.0385	47%	1.41	179%
ROC Window	2.5%	BaseplusAll	No Commissions	1971.02	2003.09	-1	60	47%	-0.0385	47%	2.13	450%
ROC Window	2.5%	BaseplusBF	High Commissions	1971.02	2003.09	-1	60	61%	0.0287	17%	0.60	70%
ROC Window	2.5%	BaseplusBF	Low Commissions	1971.02	2003.09	-1	60	61%	0.0287	17%	1.79	454%
ROC Window	2.5%	BaseplusBF	No Commissions	1971.02	2003.09	-1	60	61%	0.0287	17%	2.64	1787%
ROC Window	2.5%	BaseplusFunda	High Commissions	1971.02	2003.09	-1	60	62%	0.0566	23%	1.20	199%
ROC Window	2.5%	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	60	62%	0.0566	23%	1.97	759%
ROC Window	2.5%	BaseplusFunda	No Commissions	1971.02	2003.09	-1	60	62%	0.0566	23%	2.47	2503%
ROC Window	2.5%	BaseplusTA	High Commissions	1971.02	2003.09	-1	60	55%	0.0321	29%	2.14	432%
ROC Window	2.5%	BaseplusTA	Low Commissions	1971.02	2003.09	-1	60	55%	0.0321	29%	2.87	938%
ROC Window	2.5%	BaseplusTA	No Commissions	1971.02	2003.09	-1	60	55%	0.0321	29%	3.53	2102%
ROC Window	10.0%	Base	High Commissions	1971.02	2003.09	-1	60	62%	0.0115	13%	0.42	45%
ROC Window	10.0%	Base	Low Commissions	1971.02	2003.09	-1	60	62%	0.0115	13%	1.68	459%
ROC Window	10.0%	Base	No Commissions	1971.02	2003.09	-1	60	62%	0.0115	13%	2.50	2102%
ROC Window	10.0%	BaseplusAll	High Commissions	1971.02	2003.09	-1	60	47%	-0.0368	48%	0.81	76%
ROC Window	10.0%	BaseplusAll	Low Commissions	1971.02	2003.09	-1	60	47%	-0.0368	48%	1.55	210%
ROC Window	10.0%	BaseplusAll	No Commissions	1971.02	2003.09	-1	60	47%	-0.0368	48%	2.26	495%
ROC Window	10.0%	BaseplusBF	High Commissions	1971.02	2003.09	-1	60	61%	0.0518	18%	1.24	136%
ROC Window	10.0%	BaseplusBF	Low Commissions	1971.02	2003.09	-1	60	61%	0.0518	18%	2.34	571%
ROC Window	10.0%	BaseplusBF	No Commissions	1971.02	2003.09	-1	60	61%	0.0518	18%	3.01	1929%
ROC Window	10.0%	BaseplusFunda	High Commissions	1971.02	2003.09	-1	60	59%	0.0348	26%	1.31	241%
ROC Window	10.0%	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	60	59%	0.0348	26%	2.05	791%
ROC Window	10.0%	BaseplusFunda	No Commissions	1971.02	2003.09	-1	60	59%	0.0348	26%	2.61	2362%
ROC Window	10.0%	BaseplusTA	High Commissions	1971.02	2003.09	-1	60	56%	0.0342	36%	2.12	392%
ROC Window	10.0%	BaseplusTA	Low Commissions	1971.02	2003.09	-1	60	56%	0.0342	36%	2.98	870%
ROC Window	10.0%	BaseplusTA	No Commissions	1971.02	2003.09	-1	60	56%	0.0342	36%	3.76	1973%
Expanding Window	NA	Base	High Commissions	1971.02	2003.09	-1	60	59%	-0.0064	11%	0.26	34%
Expanding Window	NA	Base	Low Commissions	1971.02	2003.09	-1	60	59%	-0.0064	11%	1.22	379%
Expanding Window	NA	Base	No Commissions	1971.02	2003.09	-1	60	59%	-0.0064	11%	1.88	1689%
Expanding Window	NA	BaseplusAll	High Commissions	1971.02	2003.09	-1	60	54%	-0.0067	19%	0.62	78%
Expanding Window	NA	BaseplusAll	Low Commissions	1971.02	2003.09	-1	60	54%	-0.0067	19%	1.36	336%
Expanding Window	NA	BaseplusAll	No Commissions	1971.02	2003.09	-1	60	54%	-0.0067	19%	1.89	1063%
Expanding Window	NA	BaseplusBF	High Commissions	1971.02	2003.09	-1	60	62%	0.0234	11%	0.42	65%
Expanding Window	NA	BaseplusBF	Low Commissions	1971.02	2003.09	-1	60	62%	0.0234	11%	1.27	482%
Expanding Window	NA	BaseplusBF	No Commissions	1971.02	2003.09	-1	60	62%	0.0234	11%	1.88	2067%
Expanding Window	NA	BaseplusFunda	High Commissions	1971.02	2003.09	-1	60	63%	0.0367	13%	0.56	75%
Expanding Window	NA	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	60	63%	0.0367	13%	1.45	473%
Expanding Window	NA	BaseplusFunda	No Commissions	1971.02	2003.09	-1	60	63%	0.0367	13%	2.00	1905%
Expanding Window	NA	BaseplusTA	High Commissions	1971.02	2003.09	-1	60	58%	0.0363	13%	1.51	184%
Expanding Window	NA	BaseplusTA	Low Commissions	1971.02	2003.09	-1	60	58%	0.0363	13%	2.59	590%
Expanding Window	NA	BaseplusTA	No Commissions	1971.02	2003.09	-1	60	58%	0.0363	13%	3.49	1735%
Rolling Window	NA	Base	High Commissions	1971.02	2003.09	-1	60	60%	0.0448	12%	0.78	126%
Rolling Window	NA	Base	Low Commissions	1971.02	2003.09	-1	60	60%	0.0448	12%	1.51	548%
Rolling Window	NA	Base	No Commissions	1971.02	2003.09	-1	60	60%	0.0448	12%	2.04	1893%
Rolling Window	NA	BaseplusAll	High Commissions	1971.02	2003.09	-1	60	47%	-0.0312	49%	1.21	107%
Rolling Window	NA	BaseplusAll	Low Commissions	1971.02	2003.09	-1	60	47%	-0.0312	49%	2.04	258%
Rolling Window	NA	BaseplusAll	No Commissions	1971.02	2003.09	-1	60	47%	-0.0312	49%	2.87	576%
Rolling Window	NA	BaseplusBF	High Commissions	1971.02	2003.09	-1	60	60%	0.0702	14%	1.47	213%
Rolling Window	NA	BaseplusBF	Low Commissions	1971.02	2003.09	-1	60	60%	0.0702	14%	2.31	647%
Rolling Window	NA	BaseplusBF	No Commissions	1971.02	2003.09	-1	60	60%	0.0702	14%	2.94	1867%
Rolling Window	NA	BaseplusFunda	High Commissions	1971.02	2003.09	-1	60	60%	0.0591	22%	1.56	283%
Rolling Window	NA	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	60	60%	0.0591	22%	2.25	848%
Rolling Window	NA	BaseplusFunda	No Commissions	1971.02	2003.09	-1	60	60%	0.0591	22%	2.79	2475%
Rolling Window	NA	BaseplusTA	High Commissions	1971.02	2003.09	-1	60	48%	-0.0145	37%	1.28	140%
Rolling Window	NA	BaseplusTA	Low Commissions	1971.02	2003.09	-1	60	48%	-0.0145	37%	1.98	326%
Rolling Window	NA	BaseplusTA	No Commissions	1971.02	2003.09	-1	60	48%	-0.0145	37%	2.63	751%

Appendix 5-2 – All results, Initial/Rolling Window 120 months

	ROC Pval	Independent Variables	Commission Profile	Sample Start	Sample End	Lag	Initial / Rolling Window	Correct Signs	Market Timing Stat	Avg AdjRsq	Sharpe Ratio	Return
S&P Total Return				1971.02	2003.09		120				2.01	1122%
Tbills				1971.02	2003.09		120				51.98	325%
ROC Window	2.5%	Base	High Commissions	1971.02	2003.09	-1	120	64%	0.0059	11%	0.15	15%
ROC Window	2.5%	Base	Low Commissions	1971.02	2003.09	-1	120	64%	0.0059	11%	1.24	277%
ROC Window	2.5%	Base	No Commissions	1971.02	2003.09	-1	120	64%	0.0059	11%	2.01	1138%
ROC Window	2.5%	BaseplusAll	High Commissions	1971.02	2003.09	-1	120	48%	-0.0357	46%	0.58	40%
ROC Window	2.5%	BaseplusAll	Low Commissions	1971.02	2003.09	-1	120	48%	-0.0357	46%	1.42	136%
ROC Window	2.5%	BaseplusAll	No Commissions	1971.02	2003.09	-1	120	48%	-0.0357	46%	2.21	326%
ROC Window	2.5%	BaseplusBF	High Commissions	1971.02	2003.09	-1	120	63%	0.0191	13%	0.38	30%
ROC Window	2.5%	BaseplusBF	Low Commissions	1971.02	2003.09	-1	120	63%	0.0191	13%	1.78	282%
ROC Window	2.5%	BaseplusBF	No Commissions	1971.02	2003.09	-1	120	63%	0.0191	13%	2.82	1045%
ROC Window	2.5%	BaseplusFunda	High Commissions	1971.02	2003.09	-1	120	64%	0.0475	19%	1.12	123%
ROC Window	2.5%	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	120	64%	0.0475	19%	2.04	474%
ROC Window	2.5%	BaseplusFunda	No Commissions	1971.02	2003.09	-1	120	64%	0.0475	19%	2.66	1425%
ROC Window	2.5%	BaseplusTA	High Commissions	1971.02	2003.09	-1	120	56%	0.0219	26%	2.07	240%
ROC Window	2.5%	BaseplusTA	Low Commissions	1971.02	2003.09	-1	120	56%	0.0219	26%	2.96	524%
ROC Window	2.5%	BaseplusTA	No Commissions	1971.02	2003.09	-1	120	56%	0.0219	26%	3.77	1119%
ROC Window	10.0%	Base	High Commissions	1971.02	2003.09	-1	120	65%	0.0132	12%	0.30	24%
ROC Window	10.0%	Base	Low Commissions	1971.02	2003.09	-1	120	65%	0.0132	12%	1.72	310%
ROC Window	10.0%	Base	No Commissions	1971.02	2003.09	-1	120	65%	0.0132	12%	2.69	1258%
ROC Window	10.0%	BaseplusAll	High Commissions	1971.02	2003.09	-1	120	48%	-0.0334	48%	0.79	59%
ROC Window	10.0%	BaseplusAll	Low Commissions	1971.02	2003.09	-1	120	48%	-0.0334	48%	1.59	162%
ROC Window	10.0%	BaseplusAll	No Commissions	1971.02	2003.09	-1	120	48%	-0.0334	48%	2.37	361%
ROC Window	10.0%	BaseplusBF	High Commissions	1971.02	2003.09	-1	120	64%	0.0591	15%	1.22	102%
ROC Window	10.0%	BaseplusBF	Low Commissions	1971.02	2003.09	-1	120	64%	0.0591	15%	2.44	402%
ROC Window	10.0%	BaseplusBF	No Commissions	1971.02	2003.09	-1	120	64%	0.0591	15%	3.25	1203%
ROC Window	10.0%	BaseplusFunda	High Commissions	1971.02	2003.09	-1	120	61%	0.0321	23%	1.20	139%
ROC Window	10.0%	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	120	61%	0.0321	23%	2.11	472%
ROC Window	10.0%	BaseplusFunda	No Commissions	1971.02	2003.09	-1	120	61%	0.0321	23%	2.80	1314%
ROC Window	10.0%	BaseplusTA	High Commissions	1971.02	2003.09	-1	120	55%	0.0194	34%	2.01	208%
ROC Window	10.0%	BaseplusTA	Low Commissions	1971.02	2003.09	-1	120	55%	0.0194	34%	3.04	466%
ROC Window	10.0%	BaseplusTA	No Commissions	1971.02	2003.09	-1	120	55%	0.0194	34%	4.00	1006%
Expanding Window	NA	Base	High Commissions	1971.02	2003.09	-1	120	62%	-0.0117	10%	0.09	8%
Expanding Window	NA	Base	Low Commissions	1971.02	2003.09	-1	120	62%	-0.0117	10%	1.19	244%
Expanding Window	NA	Base	No Commissions	1971.02	2003.09	-1	120	62%	-0.0117	10%	2.00	1005%
Expanding Window	NA	BaseplusAll	High Commissions	1971.02	2003.09	-1	120	56%	-0.0105	17%	0.60	61%
Expanding Window	NA	BaseplusAll	Low Commissions	1971.02	2003.09	-1	120	56%	-0.0105	17%	1.44	268%
Expanding Window	NA	BaseplusAll	No Commissions	1971.02	2003.09	-1	120	56%	-0.0105	17%	2.06	783%
Expanding Window	NA	BaseplusBF	High Commissions	1971.02	2003.09	-1	120	65%	0.0158	10%	0.22	25%
Expanding Window	NA	BaseplusBF	Low Commissions	1971.02	2003.09	-1	120	65%	0.0158	10%	1.27	307%
Expanding Window	NA	BaseplusBF	No Commissions	1971.02	2003.09	-1	120	65%	0.0158	10%	2.02	1248%
Expanding Window	NA	BaseplusFunda	High Commissions	1971.02	2003.09	-1	120	64%	0.0082	12%	0.13	11%
Expanding Window	NA	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	120	64%	0.0082	12%	1.38	252%
Expanding Window	NA	BaseplusFunda	No Commissions	1971.02	2003.09	-1	120	64%	0.0082	12%	2.14	1036%
Expanding Window	NA	BaseplusTA	High Commissions	1971.02	2003.09	-1	120	58%	0.0186	11%	1.56	144%
Expanding Window	NA	BaseplusTA	Low Commissions	1971.02	2003.09	-1	120	58%	0.0186	11%	2.80	447%
Expanding Window	NA	BaseplusTA	No Commissions	1971.02	2003.09	-1	120	58%	0.0186	11%	3.84	1204%
Rolling Window	NA	Base	High Commissions	1971.02	2003.09	-1	120	63%	0.0376	8%	0.91	89%
Rolling Window	NA	Base	Low Commissions	1971.02	2003.09	-1	120	63%	0.0376	8%	2.11	407%
Rolling Window	NA	Base	No Commissions	1971.02	2003.09	-1	120	63%	0.0376	8%	3.01	1311%
Rolling Window	NA	BaseplusAll	High Commissions	1971.02	2003.09	-1	120	54%	0.0002	29%	1.11	101%
Rolling Window	NA	BaseplusAll	Low Commissions	1971.02	2003.09	-1	120	54%	0.0002	29%	1.97	302%
Rolling Window	NA	BaseplusAll	No Commissions	1971.02	2003.09	-1	120	54%	0.0002	29%	2.68	759%
Rolling Window	NA	BaseplusBF	High Commissions	1971.02	2003.09	-1	120	62%	0.0351	9%	0.68	69%
Rolling Window	NA	BaseplusBF	Low Commissions	1971.02	2003.09	-1	120	62%	0.0351	9%	1.73	339%
Rolling Window	NA	BaseplusBF	No Commissions	1971.02	2003.09	-1	120	62%	0.0351	9%	2.50	1086%
Rolling Window	NA	BaseplusFunda	High Commissions	1971.02	2003.09	-1	120	63%	0.0265	15%	0.78	71%
Rolling Window	NA	BaseplusFunda	Low Commissions	1971.02	2003.09	-1	120	63%	0.0265	15%	1.92	402%
Rolling Window	NA	BaseplusFunda	No Commissions	1971.02	2003.09	-1	120	63%	0.0265	15%	2.68	1413%
Rolling Window	NA	BaseplusTA	High Commissions	1971.02	2003.09	-1	120	54%	0.0094	15%	1.63	138%
Rolling Window	NA	BaseplusTA	Low Commissions	1971.02	2003.09	-1	120	54%	0.0094	15%	2.63	366%
Rolling Window	NA	BaseplusTA	No Commissions	1971.02	2003.09	-1	120	54%	0.0094	15%	3.46	884%

Less sensitive break detection (ROC pval = 2.5%)

All ROC window based models' performance

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	58%	6%	0.0134	0.0308	24%	13%	1.79	0.96	635%	671%

ROC window based model performance by independent variable set

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	62%	2%	0.0011	0.0052	12%	1%	1.09	0.81	560%	648%
BaseplusAll	48%	1%	-0.0371	0.0015	47%	0%	1.40	0.70	198%	161%
BaseplusBF	62%	1%	0.0239	0.0053	15%	2%	1.67	1.01	611%	683%
BaseplusFunda	63%	1%	0.0520	0.0050	21%	2%	1.91	0.64	914%	910%
BaseplusTA	56%	0%	0.0270	0.0056	28%	2%	2.89	0.69	893%	677%

More sensitive break detection (ROC pval = 10%)

All ROC window based models' performance

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
ROC Window	58%	6%	0.0186	0.0310	27%	13%	2.07	0.93	671%	676%

ROC window based model performance by independent variable set

	AvgOfSign Test	StDevOfSign Test	AvgOfMarket Timing Stat	StDevOfMarket Timing Stat	AvgOfAvg AdjRsq	StDevOfAvg AdjRsq	AvgOfSharpe Ratio	StDevOfSharpe Ratio	AvgOfReturn	StDevOfReturn
Base	63%	2%	0.0124	0.0010	13%	1%	1.55	1.01	700%	821%
BaseplusAll	48%	1%	-0.0351	0.0018	48%	0%	1.56	0.68	227%	171%
BaseplusBF	63%	1%	0.0554	0.0040	17%	2%	2.25	0.86	724%	713%
BaseplusFunda	60%	1%	0.0335	0.0015	24%	2%	2.01	0.65	886%	839%
BaseplusTA	55%	0%	0.0268	0.0082	35%	1%	2.98	0.82	819%	640%

6. CONCLUSIONS AND REFLECTIONS

This thesis examined a number of aspects of the technical analysis approach to forecasting financial markets. The dominant focus has been on technical analysis techniques that are used by mainstream analysts in the financial markets. This approach is mainstream for market participants, but peripheral for academic analysts. Chapter 2 shows that where academics have taken technical analysis seriously, evidence for its effectiveness is mixed. There seem to be microstructural reasons for expecting support and resistance levels to emerge in markets. Yet implementing levels within simple trading systems yields mixed results. The many published studies of mechanical moving averages and filter rules on balance suggest that they can be used to trade profitably. But doubts remain about their validity out of sample, and their robustness to reasonable assumptions about trading costs.

There remains a large gulf between the academic literature and industry practice and there are few examples of dialogue. Most analysts use judgemental rather than mechanical chart methods. Most use a combination of methods rather than a single indicator to support trading recommendations. And even within the class of mechanical statistical indicators, they use they use a much wider range of data transformations than has been considered by academic studies. This problem is not always eased by reference to industry textbooks, which make little reference to academic research, or even to the evolving discipline of Behavioural Finance, which certainly allows a role for price trends and patterns to be induced by investor "irrationality", and provides a route for future work to integrate technical analysis more closely into existing academic theory.

Chapters 3 and 4 of this thesis examine one of the more judgmental aspects of technical analysis – the popular idea that price (and time) targets can be gauged as multiples of the most recent trend. The examination of proportional phase anchoring in the Dow Jones Industrial Average in Chapter 3 is not supportive to this field of textbook technical theory. The exercise makes two methodological contributions. First, the Pagan and Sossounov (2003) approach to dating cycles in asset markets is extended. Second, a robust bootstrap methodology is developed from the ground up to examine the phenomenon. We find that the US stock market does not appear to anchor expected phases on prior cyclical phases, neither using round fractions nor Fibonacci ratios.

Having established the methodology for testing these propositions in an aggregate index, it would be of interest to extend this analysis to individual equities, commodities and especially currencies to assess the significance of proportional phase anchoring in such series. The methodology that we have developed is directly applicable to any index or cash security, such individual stocks, ETFs or currencies. Many technical analysts also analyse futures contracts in a Fibonacci context. Examining an application in this context would impose several considerations on the researcher. Examining individual contracts presents a methodological issue with the final trend phase, which of course terminates with the delivery of the contract rather than the reversal of the trend. This problem is partially answered by instead examining continuous contracts to address the problem as some analysts do in practice. There are two primary ways of concatenating contracts to create a continuous contract: splicing together each nearby futures contact as time progresses or having a continuous contract for each expiry month of an underlying instrument.

There are numerous reasons for looking at a series of concatenated December Soybean contacts, for example. The seasonality of commodities such as agricultural or energy products leads some analysts to examine only a specific contract month and exchanges to offer otherwise irregular expiry months – even if theory would suggest futures contacts should distribute temporal risk efficiently. Additionally, a trader with a longer trade time horizon may want to avoid the costs of rolling over contracts until December. Thoroughly extending the methodology employed to the Dow Jones Industrial Average to futures would therefore require application to the individual contracts minus their final trend phase, the nearby continuous contract and continuous contracts for each expiry month.

Chapter 4 examines whether individuals exhibit innate proportional phase anchoring. Again, we have introduced two methodological innovations, in the form of the forecasting survey, and the kernel density estimator bootstrap evaluation of the survey results. We find that practitioners' belief in the importance of specific ratios is to some extent true, with respondents choosing forecasts that mimic the previous trend (a ratio of 1:1) or extrapolate it (a ratio of 2:1). We also find that the format of series presentation does influence the phase anchoring of forecasts, as does subjects' cultural background, age and knowledge of technical analysis. The sample of respondents chosen (graduate finance students) is in many respects ideal since they have an understanding of market prices, but little prior knowledge of, or bias for or against, technical analysis. However, it would be desirable for future work to repeat this exercise with different respondents. This would be not only to see if the phenomenon reappears, but to see if the result is affected by older respondents. Our respondent sample was naturally biased by being young postgraduate finance students. For the same reason it would be useful to examine forecasts made by respondents that have absolutely no knowledge of finance (although an irrational heuristic was in fact employed by the postgraduate finance students), or are experienced technical analysts. Alternative presentation formats could also be used – for example, asking respondents to choose between alternative forecasts rather than allowing a free choice of forecast.

Chapter 5 addresses the criticism that academic studies do not use a rich enough characterisation of technical analysis, by testing 120 active market-timing strategies using equity fundamentals, macroeconomic fundamentals, behavioural variables and a diverse set of mainstream statistical indicators from technical analysis. Previous literature has not considered many of these variables, such as the Relative Strength Index and Directional Movement, though they are popular with practitioners. Nor have they been integrated into a linear regression framework, or one that accounts for structural breaks. We simulate investors' "real-time" trading decisions through recursive forecasting of excess returns from the Standard and Poors 500. Our recursive approach uses time-invariant rolling and expanding estimation windows alongside the conditional reverse ordered cusum method of Pesaran and Timmermann (2002). Accounting for structural instability via the ROC method does lead to improved performance and models that include technical indicators perform relatively well when faced with transactions costs.

Again, there are obvious extensions to this work. We are trading in the same assets as Pesaran and Timmermann (2002) – the Standard and Poors 500 index and T-bills – and our results need to be benchmarked against other markets and asset classes. Any traded instrument is a candidate to replace the SP500 index. Cash instruments would simply require calculation of behavioural and technical variables based on the series and selection of relevant fundamental data. Applying the strategies to futures contracts would face similar considerations to our above discussion of extending Chapter 3 to futures. The researcher would need to elect whether to use individual contracts, nearby continuous contracts or monthly continuous contracts to drive trading decisions. Any rollover costs between contracts would also need to be accounted for.

As in earlier regression models we use monthly data. While model fit is bound to deteriorate as we move to higher frequencies, this may not matter for trading purposes, and continuous testing for structural breaks may improve model stability.

There has been a recent trend towards models (and software packages) designed to forecast financial markets by combining technical indicators in complex nonlinear ways using neural networks, genetic algorithms and the like. This assumes that there is some stable underlying structure, which is too complex to uncover using conventional linear regression methods. This assumption seems at odds with the idea of changing investor behaviour that underpins a lot of technical analysis. Our results in Chapter 4 suggest that difficulties in forecasting arise not from complexity but from structural change, and that properly used – that is, controlling for structural change – statistical indicators used by technical analysts can give meaningful signals to investors.

What is known about technical analysis remains largely unintegrated into academic theory whilst the field of behavioural finance has deservedly developed into the mainstream. Behavioural theories of market behaviour are clearly rigorous when compared to the technician's textbooks. Nevertheless, there are more than casual similarities with western technical analysis and how Dow Theory views trends in markets. As Chapter 2 suggests, this perhaps provides the opportunity for future research to bring elements of technical analysis into a more rigorous conceptual framework and resolve Jegadeesh (2000)'s disappointment.

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