Magic numbers in the Dow

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Abstract

There is 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. Here we examine whether ratios of the length and duration of successive price trends in the Dow Jones Industrial Average cluster around round fractions or Fibonacci ratios. We identify turning points by heuristics similar to those used in business cycle analysis, and test for clustering using a block bootstrap procedure. A few significant ratios appear, but no more than would be expected by chance given the large number of tests we conduct.

***Keywords**: Technical Analysis, Stock Market, Forecasting, Anchoring, Stationary Bootstrap*

***JEL Classification**: C15, C53, G10*

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1. INTRODUCTION

This paper tests a popular but previously untested proposition about the behaviour of the stock market. 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 we are 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 paper falls into four sections. Section 2 below introduces our hypothesis and reviews relevant research findings. Section 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 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.

2. SUPPORT, RESISTANCE AND FIBONACCI NUMBERS

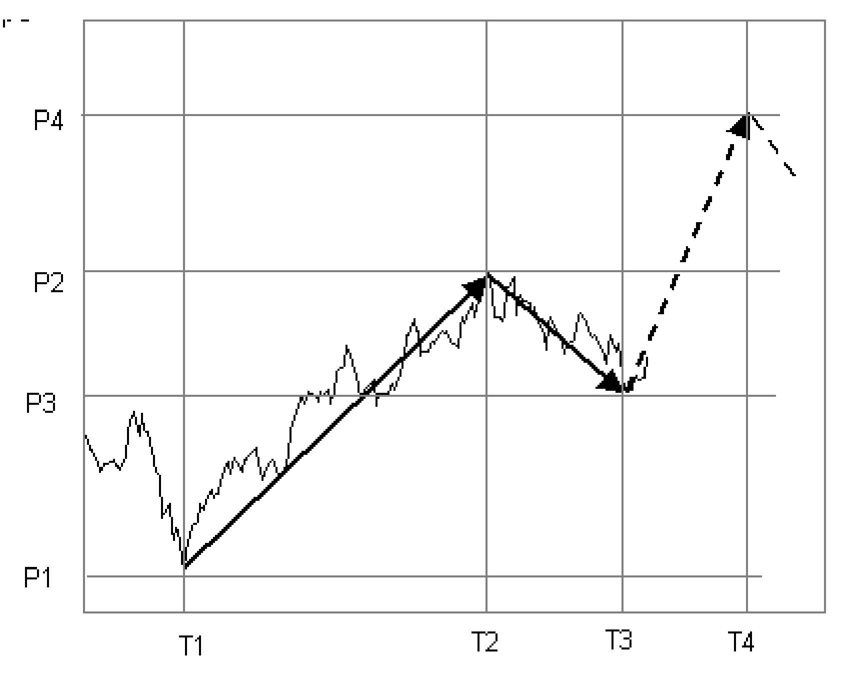
The popularity of technical analysis among market practitioners is evident from any casual reading of the financial press and the many web-based financial information services, and has been widely documented. Allen and Taylor (1992) and Lui and Mole (1998) find that technical analysis is used as a primary 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 and 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 (1999) finds evidence that this generates profits in currency markets. Brock, Lakonishok and LeBaron (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, Guillaume, Goodhart and Payne, 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 the time series of price changes after the occurrence of 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 (2000) 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 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 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 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 we 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 paper – is by means of what we term “magic numbers”. Many analysts believe that the ratio of the size of the prospective rise in price $|P4-P3|$ to the size of the preceding fall $|P3-P2|$ is not random, but is likely to lie close to one of a small number of critical ratios. 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 $|P4-P3|$ to the previous bull phase price rise $|P2-P1|$ is likely to be close to one of these key ratios. Some analysts argue that ratios of *durations* of successive runs, say $|T4-T3|/|T3-T2|$ 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. Figure 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 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"

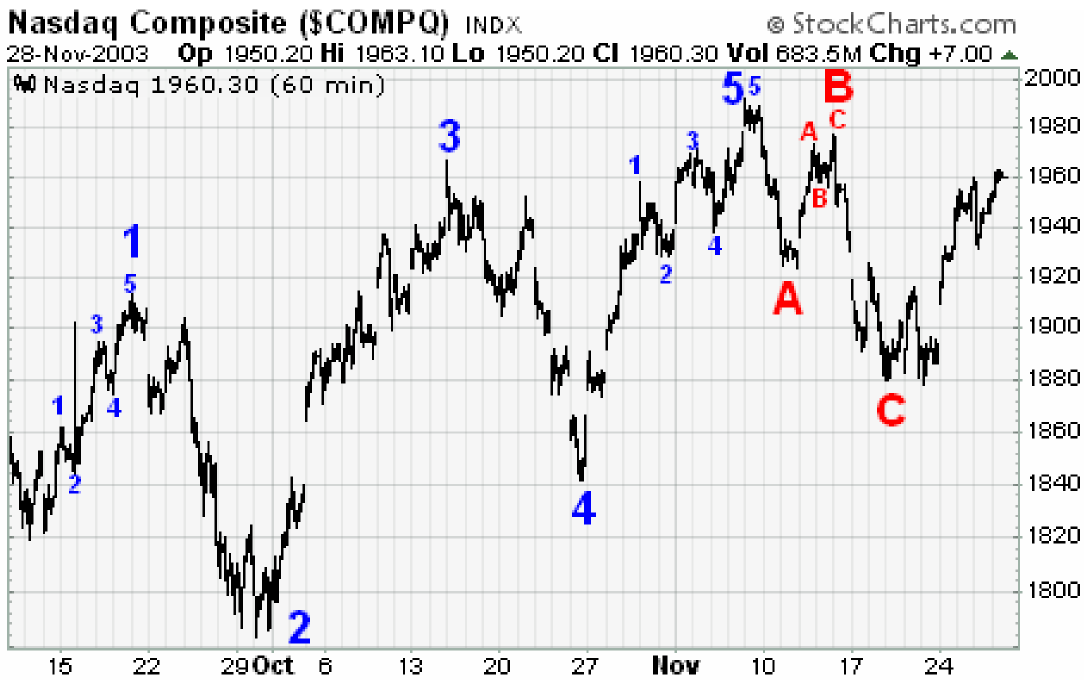
While there is clear logic in the use of round numbers or recently realised extreme values as support and resistance levels, it is not at all clear why the ratio $|P4-P3|/|P3-P2|$ should be 0.618 rather than say 0.816. One possible argument is aesthetic. The length of a Fibonacci-determined bull run "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) introduced 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 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 we also show some minor waves. In a later newsletter Elliott (1940) further claimed that the ratios of price and time retracements and projections in successive waves were likely to conform to Fibonacci ratios. So in Figure 3, we 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 we 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. 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 (2000) survey of techniques used by practising analysts.

Figure 3 – Some Elliott Waves in the NASDAQ



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 et. al. (1998) 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 we can identify the peaks and troughs the price series.

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. 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 we are interested 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. We need 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 (2004) who investigate symmetric and asymmetric filters in the range 10%-20%. Lunde and Timmerman elaborate and formalise the concept further (Table 1). 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 1 – Percentage Turning Point Filter (Lunde and Timmerman, 2004)

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, assume 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

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

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 $I_{to} = \ldots = I_{to+\tau} = 1$. 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 $I_{tmax} = \ldots = I_{to+\tau} = 0$. As per bull markets, the above holds for bear markets as:

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

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

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. 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 (1970)'s now popular rule of thumb that two or more quarter's negative growth constitutes a recession 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 steps in the Pagan and Sossounov (2003) procedure are shown on Table 2. 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, Biscarri and de Gracia (2003) and Gonzalez, Powell and Shi (2003).

Table 2 – Pagan-Sossounov (2003) procedure for identifying turning points

<u>1. Determination of initial turning points in raw data.</u>

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, **.**

<u>2. Censoring operations.</u>

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%, .

<u>3. Statement of final turning points</u>

As formally expressed in relation to monthly data by Edwards et al (2003), there is a peak at price *p* 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* 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 $A_{phase} = \dfrac{p_T - p_{T-1}}{p_{T-1}}$; ($\min(A_{phase})$ =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 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 (C) 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 we 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 troughs. Bodman and Crosby (2000) 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 (2004), 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. One is that we use 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 that we add 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 – 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 our 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 two series.

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, we find 46 cycles from monthly data, 52 from weekly and 47 from daily. Table 3 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 we agree 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 4 – 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 4. 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.

4. BOOTSTRAP ANALYSIS OF RETRACEMENT AND PROJECTION RATIOS

We aim to test 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.

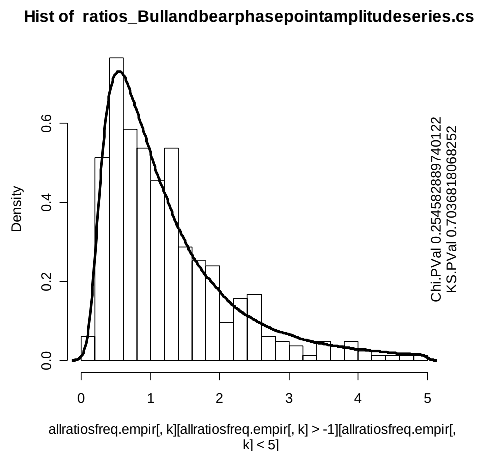
We have measured two types of ratio R, retracements and projections. Recall from the discussion of Figure 1 that a retracement is the ratio of one phase to the immediately preceding phase. There are therefore two types of retracement – a bull retracement when the market switches from a falling to a rising 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 ± ε where e 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 parameter p. 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 4 – Bootstrap distribution of bear price level retracements



Distribution of empirical versus bootstrap 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 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, we 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 4 there are slightly more retracements at 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 5 shows values the Kolmogorov-Smirnov (KS) statistic testing the null hypothesis that the whole distribution of each of the 16 ratios does not match the bootstrap distribution. The KS statistics suggest that the null hypothesis cannot be rejected for most of our ratios, but the results do tend towards the probability that the empirical distributions match the bootstrap distributions. One of the 16 statistics is significant at 90% and 14 statistics give at least a 50% chance that we can reject the null of inequality. One 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 5 – p-values from Kolmogorov-Smirnov tests for equality 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 testing for significant similarity 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. Values over 0.90 indicate significance at the 90% level, and values over 0.95** indicate significance at the 95% level.*

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 ± e where e = 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 .90 indicate significance at the 90% level, and values over .95 indicate significance at the 95% 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 we 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 we would expect to occur at random in such a time series. In our introduction, we noted that empirical evidence from academic studies suggests that not all of technical analysis can be dismissed prima facie. The evidence from this paper suggests that the idea that round fractions and Fibonacci ratios occur in the Dow can be dismissed.

Table 6 – p-values 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 at the 90% level, and values over 0.95** indicate significance at the 95% level.*

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