A Joint Review of Technical and Quantitative Analysis of Financial Markets Towards A Unified Science of Intelligent Finance

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Abstract
This paper presents a joint review on professional technical analysis and academic quantitative analysis of the financial markets, aiming at bridging the deep gulf between the two fields and unifying them under a general science of intelligent finance or financial intelligence. While econometricians and econophysicians have recently re-examined technical analysis, most of their effort is focused on chart patterns and technical indicators, leading to some simplicity impression of technical analysis. In our view, the most valuable core and also the hardest part of technical analysis is the fractal and quantum nature of Elliott waves and Gann price-time cycles and angles. On the quantitative analysis side, since Mandelbrot's discovery of fractals in financial time series, both empirical and fundamental progresses have been made, mainly in the last decade, including a third-order power law asymptotic behavior in return distribution, an accelerated crossover from the power law towards a Gaussian, a theoretical framework of crashes as critical points, and multi-agent game models of the financial markets. Inspired by these developments from the two fields we point out the possibility of developing an adaptive computational model of Elliott waves and Gann price-time cycles and angles using multilevel power laws, log-periodicity and instantaneous phase estimation.

Keywords: Review, technical analysis, quantitative analysis, financial market, stock market, intelligent finance, Elliott waves, Gann price-time cycles and angles, fractal, quantum, power law, log-periodicity, critical point, instantaneous phase.

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1. Introduction

Stock market and other associated financial markets provide the central structure and mechanism of the capitalist system. Stock market plays primarily two roles in the modern capitalist society: as the money flow network and the information flow network of the economy. Finance is essentially a matter of information processing and decision making, and successful finance is all about intelligent information processing and rational decision making. Considering the ease of accessibility by people from all walks of life, stock markets have become the last battlefield of the civilized mankind where loss may not correspond to loss of blood or physical life, but definitely to loss of wealth or bankruptcy of financial life. However, the complexity of stock market should not be underestimated ever. There are basically two reasons for this: first, stock market is virtually a full reflection of the economy and politics, domestic and global, and we must assume we do not have the mathematical and computational capability yet to model the global economy and politics as a whole in the foreseeable future; second, the participants in the stock market come from all walks of life, although human nature tends not to change, there are, however, more and more shrewd players with high-level natural intelligence and educated players equipped with 'rocket science' and back-tested financial engineering. These artistic or scientific players, if they can command large amounts of money, will tend to change the dynamics of the financial markets, which tends to defy various predictive models learned from the historical data.

Therefore, our view of finance is that the financial markets are always in a flux of movement consisting of multilevel swings and momentums driven by endogenous dynamics and exogenous shocks, impacts or other influences. Here we use the word momentum, in contrast with swings, to refer to any abrupt price movement which cannot be expressed in continuous analytical forms. Momentums may be caused by endogenous dynamics or by exogenous forces. Quite notably in the modern finance, there are two distinctive groups of players or participants: group 1 – the professional money managers and traders from large financial institutions and individual private investors or traders, group 2 – mainstream econometricians and recently emerged econophysicians as academic researchers and advisers to financial institutions. There is a deep gulf between the two groups of players and researchers. The two groups use different languages so they often do not truly understand each other, and they often underestimate the value of the knowledge, either empirical or scientific, of the other group. Each group has developed its unique systems of knowledge, skills and tools, which can not be replaced by the other group immediately. Technical analysis of the financial markets is the art and empirical science developed by professional traders for studying market action, primarily through the use of price charts, for the purpose of forecasting future price trends and maintaining an investment and trading plan. Technical analysis provides a single set of techniques for investing and trading most financial markets, including stocks, bonds, commodities, currencies and their futures. Quantitative analysis of the financial markets, is a discipline of science for discovering and developing computable mathematical models of the financial markets which can predict the future market behavior consistently and systematically whenever possible. In comparison with visual technical analysis, quantitative analysis of stock market seeks a statistical edge in outperforming the market average as represented by a benchmark index. However, it should be kept clear that technical analysis due to its visual and qualitative nature still plays a central role in professional trading and investment, and provides a main source of empirical inspirations to the development of quantitative analysis.

This paper presents a joint review on professional technical analysis and academic quantitative analysis of the financial markets, especially the stock market, with an intention of bridging the deep gulf between the two fields and unifying them under a general science of intelligent finance or financial intelligence. This review serves the purpose of clarifying the state of the arts and background for our Swingtum theory as a computational model of market dynamic swings and physical cycles in terms of fractals and statistical and quantum mechanics. The details of the Swingtum theory is offered in a companion paper [Pan 2003]. However, it must be pointed out that we do not intend to provide a comprehensive review of the literature on econometrics, mathematical finance, quantitative finance, financial engineering, econophysics, or signal processing for trading. Finance has become the mankind's largest discipline as many brightest researchers from virtually every science and engineering discipline have gathered into this arena, and it is almost impossible to read all the publications, not to mention the difficulty in recognizing the importance of each published work. We shall only mention the literature which we consider most relevant to this work in our best knowledge wherever required.

2. From Efficient Market Hypothesis To Swing Market Hypothesis

The absolute prerequisite for developing any computational predictive model of the financial markets is that the market be inefficient thus predictable at least some perceivable times. There are basically two opposite views on the predictability of the financial markets: the first is expressed in the Efficient Market Hypothesis (EMH) popularly held by many mainstream economists; the second is just all possible opposite views, which we may collectively call the Inefficient Market Hypothesis (IMH).

EMH represents a long-standing conventional view of the mainstream economists starting from Bachelier's "Theory of Speculation" (1900), through Kaynes' "animal spirits" driving markets (1936) and Nobel Laureate Harry Markowitz (1959)'s wheels of chance, up to the famous Black-Scholes option pricing model (1973). Basically, EMH views asset prices and their associated returns from the perspective of the speculator – the ability of an individual to profit on an asset by anticipating its future value before other speculators do. Markets were consequently assumed to be "efficient" meaning that prices already reflected all current information that could help anticipating future events. Therefore, modeling is only possible on the speculative, stochastic component, but not the changes due to changes in value. Under the EMH, the stochastic process of market returns can be modeled as uncorrelated random walk with independent, identically Gaussian distributed (iid) random variables. As market returns were modeled as "white" noise, then they are the same at all trading or investment horizons.

However, later studies starting from Mandelbrot (1963) and recent investigations such as Lo and MacKinley (1988), and more substantially by physicists such as Mantegna and Stanley (1995), Sornette et al (1996), Gopikrishnan et al (1999), Plerou et al (1999), show that the distribution of returns has pronounced tails in striking contrast to that of a Gaussian and there are more complicated statistical regularities in prices. The statistical results obtained from sufficiently large data sets are sufficiently strong evidence to support the aforementioned opposite model – the IMH, that is, financial markets are at least not always efficient, the market is not always in a random walk, and inefficiencies indeed exist.

Nonetheless, the EMH is not completely wrong. From both the statistical studies and professional trading experiences, a realistic hypothesis on the stochastic process nature of markets can be postulated in a Swing Market Hypothesis that markets are sometimes efficient and other times inefficient. Or in other words, the markets have two and only two general modes: efficient and inefficient, and the markets tend to swing between these two modes intermittently. Note that each mode may comprise multiple regimes. The swing between the efficient mode and the inefficient mode may correspond to shifting among different market regimes. It has been realized that predicting regime shift is the first and most difficult problem which has to be addressed before making more specific prediction on the future market movements. This Swing Market Hypothesis (SMH) shall form a cornerstone of the Swingtum model of stock markets (Pan 2003). It should be pointed that the EMH, though not always valid, nevertheless, provides essential reference points such as equilibriums of the markets, upon which more realistic market models can be developed.

The SMH provides only the necessary condition for the justification of any market model to be worthy and useful. The sufficient condition should be that inefficiencies of markets should be big enough so that financial engineering systems such as trading systems can sufficiently quickly and reliably capture the inefficiencies in order to generate net profits on a consistent basis. The first half of this sufficient condition has been validated by the consistent out-performance of a number of the world greatest money managers over all the benchmark indices such as S&P 500 for US stock markets. For example, an investment of US$1,000 in Soros's investment fund made in 1969 would be worth more than $1.3 million in 1996 – a staggering annual compound growth rate of 35 percent. In one monumental day in 1992, Soros racked up profits totaling about US$1 billion against the British sterling. In recent years, Jack Schwager (1993, 1995, 2001) reported his interviews with a number of America's top traders of stock markets and other financial markets. While many of these interviewed traders may have not traded a large amount of money on the scale of Soros's fund, many of them have achieved an average annual return from 30% up to 500%, and some have been able to maintain their triple-digit gains as long as five years in a row. There is almost no need to mention the success story of Warren Buffet, the world wealthiest billionaire in history to amass his fortune of over US$30 billion entirely through shrewd investing. For about 50 years since 1950s, he has realized compound annual rates between 20 and 30 percent. An investment of US$10,000 invested with Buffett in 1965 would be worth $10.6 million in 1994 while the result with S&P 500 would be only US$156,000. Of course, both Warren Buffett and George Soros and other top traders reported by Schwager and other authors are great artists of trading and investment, they rely on their domain-specific knowledge and hard-earned experiences, using charts and technical analysis, fundamental analysis, and mass psychology. Most of them have not relied on sophisticated mathematical models for their trading or investing businesses. These real human traders or investors are the definite confirmative evidence to the first half of the sufficient condition. The second half of this condition has also been validated by modern financial engineering systems. Since the publication of the Black-Scholes option pricing model (1973), large banks and other financial institutions have developed sophisticated computerized financial engineering systems implementing well-founded statistical arbitrage and hedge strategies. These systems are not only successful, but they have become the infrastructure of the modern global financial systems. However, almost none of the world top traders or investors or successful financial engineering system developers have ever published their theories, models, approaches or systems with sufficient details due to the highly commercial nature of their private knowledge. Nevertheless when depression or market crash come, most professional money managers or private traders still experience substantial losses. This keeps reminding us that the financial markets are complex evolving systems, not only we have not understood their complex dynamics completely, but also their dynamics may keep changing, which forever demands continuing research and developing adaptive engineering systems of intelligent finance.

3. Professional Technical Analysis of Stock Markets

Professional traders and investors fighting in the forefront of the tough game of the stock market and other financial markets have developed two broad approaches to the stock market: technical analysis and fundamental analysis.

2.1 Fundamental versus Technical Analysis

Fundamental analysis relies on economic data and focuses on the economic forces of supply and demand that cause prices to move higher, lower, or stay the same. The fundamental approach examines virtually all of the relevant factors affecting the price of a market such as sales, earnings, dividends, interest rates, company management, sector rotation, and so forth, in order to determine the intrinsic value of that market. The investment decision is based on the relativity of the intrinsic value versus the price: if the intrinsic value is under the current market price, then the market is overpriced, and should be sold; if the price is below the intrinsic value, the market is undervalued and should be bought. Benjamin Graham (1934, 1949) proposed the "Margin of Safety" as the central concept of value investment: "An investment operation is one which, upon thorough analysis, promises safety of principal and a satisfactory return. Operations not meeting these requirements are speculative." Warren Buffett's extraordinary success (Buffett and Clark 2002) has provided the sufficiently convincing evidence to the validity of the value investment principles for the medium to long-term time horizons usually ranging from 1 year to 10 years. However, the market has become more volatile in the last 2 decades as more investors have become better educated, better equipped with advanced technologies, and more focused on the short term. The fundamental supply-demand equilibrium does provide a ground level to the price in general, but its support to the price is found to be indirect, or often far from direct. There are many other stronger factors affecting the price more directly. Data sources for fundamental analysis are irregular and sometimes not reliable due to possible manipulations. Probably the most serious disadvantage of fundamental analysis is that there is too much time lag to be useful for short-term traders. However, automated news monitoring and analysis can be considered as an area of real-time fundamental analysis and could be extremely important and useful, but which has yet to be developed.

Professionals have observed through their trading experience that investors perception to the fundamental factors and mass psychology of greed and fear are the more direct forces driving the price movement. Technical analysts believe that market action discounts everything, and charts do not lie. Therefore, technical analysis relies mainly on the regular price data as the main data source. The fundamental tenet of technical analysis is that the market is primarily driven by mass psychology, human nature tends not to change, and history repeats itself. Since the first publication of Robert Edwards and John Magee's classic "Technical Analysis of Stock Trends" (1948), technical analysis has grown from an arcane practice to a widely accepted means of predicting likely future market movement. John Murphy (1999) provided a comprehensive, yet concise coverage to the concepts of technical analysis and their applications to the financial markets.

However, among some circles of fundamental analysis and econometrics, technical analysis is known as "voodoo finance." Burton Malkiel (1999) in his influential book "A Random Walk down Wall Street" concludes that "under scientific scrutiny, chart-reading must share a pedestal with alchemy." Recently, technical analysis has been re-examined by engineers, econometricians and econophysists such as John Ehlers (2001), Lo et al (2000), Ilinskaia and Ilinski (1999). While they have recognized the validity and usefulness for some technical analysis techniques, most of them focused mainly on chart patterns and technical indicators. In our view, most of these newly emerged efforts have not yet targeted to the most valuable core of technical analysis – the fractal and geometrical or quantum nature of Elliot waves and Gann price-time cycles and angles, which are, however, the hardest parts.

In our view, despites of an already large and ever expanding literature on technical analysis, in particular hundreds of technical indicators, classical technical analysis can be divided into only three fundamental components: Dow trends, Elliott waves, and Gann cycles and angles, plus one computational component – technical indicators, and one visual component – chart patterns.

2.2 Dow Theory of Trends

From 1884 on, Charles Dow published his ideas about stock market trends in a series of editorials he wrote for the Wall Street Journal, which has been known collectively as the Dow Theory, which is the origin of all technical market studies. Dow did not think of his "theory" as a device for forecasting the stock market, but rather as a barometer of general business trends. Dow is believed to have been the first to make a thoroughgoing effort in express the general trend of the stock market in terms of the average price of a selected few representative stocks. Now the Dow Jones Industrial Average Index made up of only some 30 largest stocks has been and still is the most influential index of the world.

Dow Theory holds the following views on the stock market behavior:

(1) The average discount everything, meaning that the sum and tendency of the transactions on the Stock Exchange represent the sum of all Wall Street's knowledge of the past, immediate and remote, and applied to the discounting of the future. This applies to market averages, as well as it does to individual liquid markets.
(2) The market has three trends – primary, secondary and minor. Dow defined an uptrend as a situation in which the market has successive rallies each closes with higher high and higher low, and vice versa for a downtrend. The primary trend represents the tide lasting for more than a year and possibly for several years. The secondary trend represents the waves – the corrections that make up the tide, usually lasting three weeks to three months. The minor trend represents the fluctuations in the secondary trend, behaves like ripples on the waves, usually lasting roughly a few days to two weeks.
(3) The primary trend has three phases: an accumulation phase, a public participation phase, and a distribution phase. The accumulation phase corresponds to informed or planned buying by the most astute investors. Then comes the public participation phase where most technical trend followers begin to participate after seeing the prices begin to advance rapidly and business news improves. This phase naturally leads to the market boom or bubble which will then bust or crash or gradually decline through the last phase where the same informed investors begin to "distribute" before anyone else starts selling. In fact, we should add a fourth phase: the crash or decline of the market which follows the essential completion of informed investors distribution.
(4) The primary trend must be confirmed by different but mutually confirming averages (such as the Industrial and Rail Averages in Dow's time) and by volume. In particular, volume should expand or increase in the direction of the major trend.
(5) A trend should be assumed in effect until definite signals are observed that it has reversed. This is equivalent to Newton's first law of motion which states that an object in motion tends to continue in motion until an external force causes it to change direction. This tenet forms much of the foundation of modern trend-following approaches.

For the ease of the future discussion, we shall call these five tenets respectively (1) the average discounting principle, (2) the multilevel trends principle, (3) the multiple phases principle, (4) the trend confirmation principle, and (5) the trend inertia principle. We can clearly recognize that these five principles of Dow Theory provide much of the most important foundations for technical analysis, which have stood the test of the time for more than a hundred years.

However, the Dow Theory has been criticized for being too late in generating signals and too subjective and imprecise in identifying multilevel trends. These criticisms are generally right on the weakest points, for which Elliott wave theory and Gann price-time cycles and angles represent substantial improvements in the sense of finer structuring and predictive time leading.

2.3 Elliott Theory of Waves

Very much influenced by the Dow theory of trends, Ralph Nelson Elliott took one big step further, formulated his observations of the wave principle during a long period of convalescence during the 1930s into the now called Elliott Wave Theory (Prechter 1996, 2002). Mathematicians today would recognize the Elliott waves discovered in the 1930s as fractals discovered some 40 years later by Mandelbrot (1982).

Elliott observed waves of different levels throughout the unfolding of a trend in a given time frame. There are certain patterns, significant price ratios and time ratios in the waves. The theory can be summarized in a few basic principles:

(1) Action of a trend is followed by reaction of retracement.
(2) There are five waves in the direction of the main trend, usually labeled as waves 1, 2, 3, 4, 5, followed by three corrective waves, called waves a, b, c. Waves 2 and 4 are corrective to waves 1 and 3, and waves b and c are corrective to wave a and b respectively. Such a sequence of waves is also called a 5-3 move.
(3) A 5-3 move of 8 waves completes a cycle, which then becomes 2 subdivision of the next higher 5-3 move. This is the key characteristic of a fractal as we know today.
(4) The underlying 5-3 move pattern tends to remain constant, though the price range and time span of each wave may vary.

Elliott recognized that the 5-3 move pattern was fairly regular, which allowed for a certain degree of predictability of future market behavior. While he did not mention any stringent rule when applying these principles, later market analysts developed the following three "inviolate" rules:

(1) Wave 2 cannot retrace past the beginning of wave 1.
(2) Wave 3 cannot be the shortest of the three impulse waves 1, 3, and 5 in the five wave sequence.
(3) Wave 4 cannot overlap or trade into the territory of wave 1.

If any of these rules are violated, the wave structure as labeled is considered incorrect and must be re-evaluated. In reality, these "inviolate" rules should be considered in a relative sense. If these rules are met, it only show the pattern is obvious and the predictability is relative high. In a broader view, the market may not be unfolding in a clearly recognizable pattern within the context of the Elliott wave principles, thus one should not force a wave count just for the sake of having a wave count.

Market analysts have also discovered that price retracement ratios such as wave 2 to wave 1, wave 4 to wave 3, and waves a-b-c relative to waves 1-2-3-4-5 are distributed, more often than not, around a few Fibonacci numbers and common numbers: 38.2%≈38%, 50%, 61.8%≈62%, 100%, 162%, 200%, etc. Careful examination shows that these numbers are in fact approximately some integer powers of scale factor 2: $3/2^3$=37.5%≈38%, $4/2^3$=50%, $5/2^3$=62.5%≈62%, and so forth. It means that the Elliott waves are indeed fractals that have certain scale invariance properties.

Time retracement ratios also follow the similar distributions, but are considered by some Elliotticians to be less reliable in market forecasting. It appears that Gann theory of cycles and angles provides a much finer treatment of the time relationships in the market behavior patterns.

2.4 Gann Theory of Cycles and Angles

William Delaware Gann was a pioneer in the area of time-price geometry of market behavior [Gann and Allery 1951]. With a mathematical background, Gann was both a real trader and a predicator. As a trader, Gann made real big money at his time between 1910s and 1940s. And as a predictor, he reputedly had the knowledge to forecast the price and time of yearly high and low for commodities and stocks a full year in advance. Gann developed several unique techniques for studying price charts, mainly dynamic analysis of time and price relationships and geometric angles, which we collectively call Gann theory of cycles and angles. Gann and Elliott shared some similar beliefs about market activity. While Gann believed that a bull or bear trend took 3 or 4 sections to complete the move, Elliott believed there were 3 impulsive waves in the direction of trend, with the possibility of an extended 5^{th} wave to give Gann's 4^{th} section. In contrast, while Elliot believed in Fibonacci numbers as most common retracement ratios, Gann believed in the integer powers of scale factor 2 as mentioned above. Especially, Gann believed the retracement time ranges follow this series of common ratios and the time relationship is equally or even more important than price relationship in predicting market reversals. The central idea of the Gann theory is that there exist some fundamental symmetries between time and price ranges. However, it is known that the Gann theory is the most mysterious and reported the most accurate one of the classical technical analysis, which has been tested by time and trading practice.

Gann recognized that cycles were a clear existence in market activity, and he considered that cycles may be caused by cycles of the physical universe mediated through the biological and cognitive cycles of human beings. He apparently recognized both seasonal physical cycles and market dynamic cycles.

We consider Gann's unique contribution should be geometric notions now called Gann angles and other elaborations called Gann fans, Gann grids, and Cardinal squares. Gann angles are specified by price and time ranges such as "a x b" where a is the amount the line rises in price and b the time period in which the rise occurs. Gann identified nine significant angles, 1x8, 1x4, 1x3, 1x2, 1x1, 2x1, 3x1, 4x1, 8x1, with the 1x1 being the most important. Gann angles are drawn from the most recent lowest low or the highest high toward the future. Using Gann angles, the space of price and time can be divided into Gann grids. The market is most likely to move along Gann grid lines.

Robert Miner (1997), one of most active instructors and practitioners of Gann and Elliott theories and also the first place winner of the 1993 Robbins World Cup Championship of Futures Trading, proposed an analogy of market movement with solar or atomic particle model. He considers that price must travel through the "space" between the time and price levels or orbits, which are the significant support or resistance levels. If the market exceeds a projected dynamic price level or time range, the odds favor that the market will continue to at least the next projected level. In other words, the market typically "jumps" from one level to another, very much like electrons jump between energy levels in the atomic particle model.

Gann theory of price-time symmetry and geometric angles and Miner's analogy to the atomic particle model have inspired us to move one step further in formulating the concept of quantum price-time space of market activity (Pan 2003).

2.5 Technical Indicators: Modes, Trends, Cycles, Volatility

A technical indicator is a function of the market time applied to the price and/or volume time series data of a security or a market. The function represents a method of quantitative analysis of price over time or volume, which usually takes the form of a simple mathematical formula designed to highlight specific characteristics and provides signals to help forecast market movements. In terms of signal processing, a technical indicator is just a filter over a price and/or volume time series (signals). Each indicator offers a specific perspective from which the market action can be analyzed and changes in prices can be anticipated. No indicator is right all the time, and all the different indicators may contradict each other most of the time. This is just normal. The prerequisite for applying or interpreting any indicator is to understand the scale level and range of the time frame. Note that any technical indicator is applied only to a predefined time frame and scale level. Therefore, its interpretation should also be limited to that time frame and scale level.

There are a great number of technical indicators (Achelis 2000), each implementing an empirical or ad hoc idea of quantitative analysis. Selecting a minimal set of indicators to form a particular trading system is thus often an art rather than a science. There is a great distance yet to travel from individual indicators to a complete trading system which implements a complete computational approach to market analysis and trading.

Most technical indicators fall into four general categories: market mode, trend, cycle and volatility:

(1) Market mode indicators: Theoretically, there should be at least one indicator which can detect the current dominant mode of the market to be either in a trend mode, or a cycle mode, or in a side way, or in a mode change, e.g. from a trend mode to a cycle model. In reality, it appears that detection of the market mode and mode change is probably the hardest thing to do, and any single indicator may not be sophisticated enough to tackle this problem. However, this can be done by the relative strength of trend indicators versus cycle indicators. If trend indicators produce clear and strong signals while cycle indicators produce ambiguous output, the trend mode should be assumed, and vice versa. In this sense, John Ehlers's MESA filter (maximum entropy spectrum analysis) (1992, 2002) can be considered as a market mode indicator, but of course, applicable only on the given time scale and frame. More sophisticated techniques for market model detection may include detection of low-level chaos or multifractals in the price time series data, which however is far beyond the scope of technical indicators.

(2) Trend indicators: trends can be detected simply by various moving average indicators, including Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA) and other variations. SMAs and

WMAs are finite impulse response filters, and EMAs are infinite impulse response filters. Crossovers of different moving average indicators of different bandwidth signal the start or end of a trend or a trend reversal. In terms of fractals, trends are synonymous to persistence.

(3) Cycle indicators: Cycles usually occur during an accumulation phase before an uptrend or during a distribution afterwards. In fact, retracement waves throughout a trend development may also be considered as cycles. However, in technical analysis terms, cycles are only referred to trendless periods. Popular cycle indicators include various stochastic oscillators such as Momentum Indicator, Relative Strength Index (RSI), Stochastics (K%D), Moving Average Convergence/Divergence (MACD). In contrast, Ehlers's Sinewave indicator is an adaptive cycle filter well founded on signal processing principles.

(4) Volatility indicators: Under the assumption of the normal distribution for the market returns, the volatility of the prices is best measured by standard deviation. Therefore, Bollinger Bands is commonly used as the best choice for the volatility. Bollinger Bands are plotted at standard deviation levels, usually 2 times, above and below a moving average. Since standard deviation is a measure of volatility, the bands are self-adjusting, widening during volatile markets and contracting during calmer periods.

For visual chart analysis, a minimal set of indicators should include three indicators, one for each of the above mentioned categories, e.g. Crossover of two Moving Averages of different lengths as a trend indicator, RSI or Sinewave as a cycle indicator, and Bollinger Bands as volatility indicator. In addition, either one is trading individual stocks or an stock index derivative, it is always important and necessary to keep a global view on the whole stock market, therefore, one should always have one or more market breadth indicators such as Advance/Decline Ratio or Advance/Decline Volume Ratio, New Highs/Lows Ratio, etc.

2.6 Chart Patterns

Chart patterns are distinguished between two collections: candlestick patterns and general chart patterns. Each candlestick corresponds to a time unit, most commonly a day for general investment, or a minute for intraday trading. In default, we only consider daily charts. The prerequisite for considering any chart pattern is the context of the market mode. In particular, most of the studied chart patterns fall within two types: reversal patterns and continuation pattern. The more specific prerequisite for any reversal or continuation pattern is the existence of a prior trend or the current trend.

A candlestick pattern has a limited time frame of 1 to 5 days, or say, within a week. Most popular candlestick patterns (Morris 1995) include:

(1) Bullish reversal patterns: Bullish Engulfing, Piercing Pattern, Bullish Harami, Hammer, Inverted Hammer, Morning Star, and Bullish Abandoned Baby.

(2) Bearish reversal patterns: Bearish Engulfing, Bearish Abandoned Baby, Bearish Harami, Dark Cloud Cover, Evening Star, Shooting Star.

A general chart pattern has a much longer time frame, ranging from the minimum of 2 weeks up to a maximum of 6 months. In general, a time frame of 1-3 months should be considered. There are general tendencies for reversal patterns: The first signal of an impending trend reversal is often the breaking of an important trendline; The larger the pattern, the greater the subsequent move; Topping patterns are usually shorter in duration and more volatile than bottoms; Bottoms usually have smaller price ranges and take longer to build; and volume is usually more important on the upside. Common chart patterns include:

(1) Bullish reversal patterns: Triple Bottoms, Double Bottoms, Head-and-Shoulder Bottoms, Rounding Bottoms.
(2) Bearish reversal patterns: Diamonds, Head-and-Shoulder Tops, Triple Tops, Broadening Tops, Double Tops.
(3) Bullish continuation patterns: Descending Triangles, Rectangles, Ascending Triangles, Symmetrical Triangles, Ascending Scallops, Descending Scallops, Flags, Pennants, Measure Bull Moves..
(4) Bearish continuation patterns: Symmetrical Triangles, Ascending Triangles, Descending Triangles, Descending Scallops, Ascending Scallops, Flags, Pennants, Measured Bear Moves..

Bulkowski (2002) provides statistics on the performance for each of some 19 most common chart patterns.

4. Academic Quantitative Analysis of Stock Markets

It is well known that grand masters of professional fund management such as George Soros, Warren Buffet and Peter Lynch have solely relied on their intuitions and insights, rather than sophistical mathematical models, in making trading or investment decisions. Technical analysis backed by fundamental analysis is a culmination of empirical discoveries and knowledge forged by such professional intuitions and insights. Considering human intelligence is still much higher than computational intelligence in visual recognition and qualitative thinking, it is no wonder that technical analysis should be respected as a high art but quite likely on the sound basis of a science which has yet to be formulated.

Quantitative analysis of the financial markets, also briefly called quantitative finance or financial engineering, is a discipline of science for discovering and developing computable mathematical models of the financial markets which can predict the future market behavior consistently and systematically whenever possible. In comparison with visual technical analysis, quantitative analysis of stock markets seeks a statistical edge in outperforming the market average as represented by a benchmark index. However, it should be kept clear that technical analysis due to its visual and qualitative nature still plays a central role in professional trading and investment, and provides a main source of empirical inspirations to the development of quantitative analysis. A comprehensive review on quantitative analysis is certainly beyond our reach. Instead, in the following, we shall only summarize recent discoveries on the statistical properties of stock market indices and prices and recent developments of random process models and agent-based evolutionary models. We are inspired very much by these discoveries and developments in forming our ideas underlying the Swingtum theory (Pan 2003).

3.1 Statistical Tendencies in Prices and Indices

It is natural that the science of quantitative analysis must start with addressing the statistical properties of the stock prices or market indices, in particular the distribution of price or index fluctuations. This has been a topic of active debate for several decades and a few important empirical statistical regularities have been found recently.

Let $p(t)$ be the price (or index) at time t, the relative return $R_\tau(t)$ is defined as

$$R_\tau(t) = \frac{p(t+\tau) - p(t)}{p(t)} \tag{1}$$

where τ is the time scale.In general, it is more common to use the log-return $r_\tau(t)$ defined as

$$r_\tau(t) = \ln p(t+\tau) - \ln p(t) \tag{2}$$

For small changes in $p(t)$, the log-return $r_\tau(t)$ and the relative return $R_\tau(t)$ are approximately equal.

Under the Efficient Market Hypothesis, the price changes in each unit time interval can be assumed to be independent and identically distributed (iid) with a well-defined second momentum, the central limit theorem naturally suggests that the cumulative distribution function $f(r_\tau)$ should converge to a normal Gaussian distribution for large τ (Bachelier 1900, Samuelson 1965).

However, real financial data analysis presents surprising deviations from the normal distribution: first, the convergence is very slow and thus has fat tails; and second, the distribution for smaller values of τ - less than about a month – deviates strongly from normality; third, the autocorrelation of log-returns drops down very quickly after about 15 minutes and reaches the noise level after about 20 minutes. In particular, the fat tails imply a higher probability for extreme values than for a normal distribution. This can be measured by using the kurtosis

$$k = \frac{< (r_\tau - < r_\tau >)^4 >}{< (r_\tau - < r_\tau >)^2 >^2} \tag{3}$$

which is larger than expected for a Gaussian, where $<>$ denotes a time average.

Mandelbrot (1963) and Fama (1965) showed empirical evidence that $f(r_\tau)$ was a stable Levy distribution. For random variables that are so fat-tailed that their second moment does not exist, the normal central limit theorem no longer applies. Under certain conditions, however, the sum of many such variables converges to a Levy distribution which arises from a generalization of the central limit theorem. Except for special cases, the stable Levy distributions cannot be expressed in closed form, however, they are characterized by a parameter $1 \le \mu \le 2$, where $\mu = 2$ corresponds to the special case of a normal distribution. For $\mu < 2$, however, the stable Levy distributions are so fat-tailed that their standard deviation and all higher moments are infinite. Mandelbrot and Fama measured $\mu = 1.7$ based on daily returns in commodity markets and stock markets. This result indicates that short-term stock returns are indeed ill-behaved and most statistical properties are ill defined.

The stock index movements have been studied recently by Akgiray et al (1989), Mantegna and Stanley (1995), Lux (1996), and Gopikrishnan et al (1999). The behavior is found more complicated than the stable Levy distributions. Large returns asymptotically follow a power law

$$f(r_\tau) \sim |r_\tau|^{-\alpha}, \text{ with } \alpha > 2 \tag{4}$$

Important is that with $2 < \alpha < \infty$, the second moment (variance) is well defined, which is incompatible with the stable Levy distribution. In particular, the Boston Group (Montagna and Stanley 1995, Gopikrishnan et al 1999) has studied the intraday movements of the S&P 500 index. They observed that for larger values of $|r_\tau|$, $f(r_\tau)$ approximates a power law with $\alpha \approx 3$. Thus, the mean and variance are well-defined. Furthermore, for larger time scales $\tau > 4$ days, the distribution becomes progressively closer to normal. Drozdz et al (2002) reanalyzed several characteristics established by the Boston Group, and found a significantly more accelerated crossover from the power law ($\alpha \approx 3$) asymptotic behavior of the distribution of returns towards a Gaussian, both for the US as well as for the German stock markets. It indicates a faster loss of memory with increasing time. The fact that the distribution's shape changes with time scale τ reminds us that the random process underlying prices or indices must have nontrivial temporal structure, which cannot be fully understood in terms of central limit theorem arguments, even in a generalized form.

3.2 Random Process Models of Prices and Indices

Time series of stock prices and indices have been a subject of random process models in the last two decades. There are basically three types of models: statistical autoregressive models, nonlinear dynamic models, and monolithic neural networks.

Statistical studies indicate that price fluctuations are not identically distributed, exhibiting the so-called clustered volatility, meaning that statistical properties of the distribution, such as the variance, change in time. Although the autocorrelation of log-return drops sharply to very small on time scales longer than 1 day, the volatility on successive days is positively correlated, and these correlations may remain positive for weeks or months.
Clustered volatility is an expression of the nonstationarity of financial time series, which has to be described by every random process model.

Traditional statistical models describing clustered volatility include ARCH (for AutoRegressive Conditional Heteroscedasticity) and GARCH (for Generalized ARCH) models first developed by Engle (1982). For a review of applications in finance, see (Bollerslev et al 1992; Campbell et al 1997). Typically, the goal of these models is to forecast volatility and sometimes correlations. While ARCH-type models can be effective for forecasting volatility, they are not compatible with all of the empirical statistical properties of price fluctuations.

Since Mandelbrot, several groups such as the Boston Group, Ghashghaie et al (1996), Schmitt et al (1999), Drozdz et al (1999) and Bouchaud et al (2000) largely from physics, have studied the market behavior on multiple timescales, typically based on the moments $<|r_\tau|^q>$ as a function of q and τ. They have all found approximate power-law scaling with τ, and with different slopes for each value of q. This suggests the existence of a fractal random process in terms of chaos theory. Several reports show that the slope varies nonlinearly with q, implying that the existence of multifractality in financial time series. However, Scheinkman and LeBaron (1989) showed that the claims of low-dimensional chaos in financial time series were not well-justified. Low-dimensional chaos, if existent, would imply deep structure and short-term predictability in prices, which is a very strong hypothesis. However, prediction of high-dimensional chaos can be very difficult because it requires very large data sets. One aspect of the chaotic processes in financial time series may be explained as an information cascade, in which financial agents with more capital or longer-term strategies influence those with smaller capitals over shorter time frames. This process induces a cascade of volatility. This has been confirmed by Arneodo et al (1998) through a wavelet decomposition of volatility and a mutual information analysis.

In addition to the power-law scaling, imprints of log-periodic self-similarity are found in the stock market by Sornette's group (Sornette et al 1996, Johansen and Sornette 1999, Sornette and Zhou 2002, Sornette 2003, Zhou and Sornette 2003) and Feigenbaum's group (Feigenbaum et al 1996, 2001) and confirmed by other groups (Vendevalle et al 1998; Gluzman and Yukalov 1998; Drozdz et al 1999). A large number of cases have been reported and an underlying theoretical framework of crashes as critical points has been developed based on the economic view of rational expectation bubbles. In particular, Sornette et al have proposed a model of financial crashes as critical phenomena in the statistical physics sense of critical phase transitions. In particular, they have used a form of Landau expansion as a dynamical model of a financial bubble

$$\ln p(t) \approx A + B(t-t_c)^\beta + C(t-t_c)\cos(\omega \ln(t-t_c)+\phi)) \tag{5}$$

where t_c denotes the critical point corresponding to the peak of the bubble, ω, ϕ are the log-periodicity and phase shift, $1 \le \beta \le 4$ in general, and A, B, C are constants. The same form of (5) applies to the anti-bubble but with $(t_c - t)$ replacing $(t-t_c)$. Two hallmarks of criticality are: (1) super-exponential power law acceleration of the price towards a "critical" time corresponding to the end of the speculative bubble and (2) log-periodic modulations accelerating according to a geometric series signaling a discrete hierarchy of time scales. While Sornette et al's model aims at describing stock market crashes, we have observed a spiritual and mathematical similarity or affinity between the log-periodicity and Elliott waves and Gann price-time cycles as well as Gann angles. However, one big step has yet to be taken to reach a computable statistical mechanics and quantum mechanics model of Elliott waves and Gann cycles and angles from the current status of power law scaling and log-periodicity.

3.3 Multi-Agent Game Models of Stock Markets

Stock markets and other related financial markets are complex dynamic systems whose elementary building blocks are individual traders, each making buying and selling decisions from his or her own perspective. Naturally, the most fundamental approach for modeling stock markets would be to develop computational agents simulating human traders, and then to derive the ensemble behavior of the whole market from the multi-agent trading processes. This approach has an obvious advantage of being homomorphic to the real market and thus being the most fundamental. However, it is also apparent that modern educated and artful traders commanding large sums of money may be so sophisticated that we may never be able to find out their specific trading strategies. This can become a never-ending game between human traders and computational agents which try to simulate them. Nevertheless, a lot of preliminary work has been done already in multi-agent models of stock markets which have shown significant results (Challet and Zhang 1997, Farmer 1998, Arthur 1999, Lux and Marchesi 1999, Farmer and Joshi 2002).

Agent-based models range over the whole spectrum of complexity from simple, metaphorical models such as those of evolutionary game theory to large-scale complicated simulations such as the Santa Fe Institute (SFI) stock market model (Farmer and Joshi 2002). The minority game introduced by Challet and Zhang (1997) offers possibly the simplest paradigm of the stock market as multi-agent games. At each time step, N agents choose between two possibilities: buy or sell. A historic record is kept of the number of buyers; the number of sellers is automatically determined because N is fixed. The only information made public is the most popular choice. An excess of buyers will force the price up, consequently the minority of agents who have placed sell orders receive a good price at the penalty of the majority who end up buying at an over-inflated price. This gives the game its 'minority' nature. Despite its simplicity and its metaphorical connection to markets, the minority game displays some rich behavior such as irregular fluctuations. Ferreira et al (2002) performed time series analysis of the minority game model in comparison with the S&P 500 index, and found that the full motion of the minority game is similar to that of returns of the S&P 500 index: stochastic, nonlinear and unit root stationary under certain conditions.

The SFI stock market model offers possibly the most comprehensive agent-based model of stock markets. It demonstrated that many of the nonlinear dynamic properties of real stock markets such as clustered volatility, fat tails and high volume autocorrelation, emerge automatically from the trading processes of dynamic trading agents. By replacing the synthetic price history with data taken from real financial time series, Jefferies et al (2000) found some remarkable result from agent-based market simulations that the agents can collectively learn to identify moments in the market where profit is attainable, thus indicating a real possibility of bridging the market games to real-world markets.

5. A Step Towards A Unified Science of Intelligent Finance

Professional technical analysis and academic quantitative analysis as well as fundamental analysis and mass psychology have been converging from the last decade up to now. The eventual outcome of this convergence is likely to be a unified science of intelligent finance or financial intelligence. The fundamental and exclusive reason for the finance or trading to be a specialized intelligence is because trading financial markets is a game between people and will remain as a game between human traders and intelligent trading systems. Trading financial markets is largely a zero-sum game, a minority game, an information game, and a capability game; some minority who are better informed, better knowledgeable, better disciplined, better equipped, and better capitalized should have a dominant advantage over the rest majority, and will win consistently in the long run. Though being similar to other large-scale dynamic systems such as the global weather and climate system in many aspects, the financial markets are dynamic systems whose building elements are human beings and artificial intelligent trading systems developed and supervised by human beings. Furthermore, the financial systems are open to and tightly influenced by the global economy and politics. Therefore, an objective science of finance could hardly exist, thus the best we can have might just be an empirical science and engineering of intelligent finance. This view of ours is in line with George Soros's theory of reflexivity (1987, 1994), but we truly believe that the best artificial intelligent trading systems owned only by some minority of traders will outperform the majority of human traders and other less advanced trading systems.

Profitable trading systems must be based on the existing best knowledge of technical analysis, quantitative analysis, and fundamental analysis. Our view to the culmination of these empirical sciences is structured in a market model which we call the Swingtum theory. Here we briefly summarize the essential ideas of this theory, more details of which are given in a companion paper (Pan 2003).

The Swingtum theory is based on an view that the stock market as a whole as represented by a benchmark index, such as ASX S&P 200 index for Australian stock market or S&P 500 index for US stock market, is in a constant flux of motion which is made up of four types of fluctuations: dynamic swings, physical cycles, abrupt momentums and random walks. The dynamic swings include business cycles ranging between 3-5 years, and multilevel trends or Elliott waves of different time spans. Dynamic swings have a fractal nature, and do not have a constant periodicity. The physical cycles include anniversary days – yearly cycles, monthly cycles, and weekly cycles. Each physical cycle has a relatively constant periodicity. The most notable are anniversary days and days in a week. Abrupt momentums may be caused by endogenous forces such as the critical points, or more often by exogenous forces such as news impact. Fractal dynamic swings are traditionally identified as Elliott waves, and may possibly be modeled as mathematical fractals by the power laws and log-periodicity. Physical cycles can be modeled as adaptive sine waves whose instantaneous periodicity and phase can be detected from the price time series through Hilbert transform. Abrupt momentums may possibly be modeled in chaotic patterns, which may be triggered by new impacts or invoked by instantaneous chart patterns, simply because most technical traders have acquired similar education. The geometrical nature of power laws and log-periodicity share some fundamental similarity or affinity to the Gann price-time cycles and Gann angles, which has inspired us to consider the possibility of a quantum price-time space for unfolding of Elliott waves or financial bubbles and anti-bubbles or crashes. The actual path of the market is therefore likely to be a dynamic walk through the quantum price-time space where each step is dependent probabilistically on its immediate previous steps, its history on different time scale levels, and news events.

The above review has focused on statistical and dynamical models for market analysis and prediction which corresponds to the science half of intelligent finance. The engineering half of intelligent finance should address the profitable trading strategies, techniques and implementations, which the author will cover in a future review paper.

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