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A BASIC THEORY OF INTELLIGENT FINANCE

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This paper presents a basic theory of intelligent finance as a new paradigm of financial investment. It is assumed that the financial market is always in a state of swing between efficient and inefficient modes on multiple levels of time scale; it is possible to go beyond the efficient market theory to study the dynamic evolving process of the market between equilibrium and far-from-equilibrium; there are robust dynamic patterns in this evolving process, which may be exploitable via intelligent trading systems. On the foundation of the four principles — comprehensive, predictive, dynamic and strategic, the basic theory takes the information sources into the loop as the starting points for all the market analysis, introducing the scale space of time into the pricing process analysis in order to detect and capture trends, cycles and seasonality on multiple intrinsic levels of time scale which are then used as the dynamic basis for constructing and managing portfolios. In stock markets, the theory exhibits itself in the form of an Intelligent Dynamic Portfolio Theory, which integrates predictive modeling of a bull-bear market cycle, sector rotation, and portfolio optimization with a reactive trend following trading strategy.

Keywords: Intelligent finance; financial market analysis; financial information fusion; multilevel process analysis; dynamic portfolio management; financial strategic analysis; bull-bear market cycle; intelligent dynamic portfolio theory.

1. Introduction

Among the many attributes of finance four are outstanding in modern academic and professional financial practice: (1) finance as a policy-making discipline since the financial markets serve as the central structure of modern market economy and so finance is studied to consolidate the functionalities and improve the efficiency of financial markets through market restructuring and the innovation of new financial

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products; (2) finance as an observational science for understanding the mysteries in market functionalities, risks and price behavior; (3) finance as a passive applied science for managing the risks associated with financial assets and investments; and (4) finance as an active applied science, technology and even an art for pursuing better than average investment returns. It is a matter of fact that different financial theories or empirical models or understanding can be and have historically been developed from different perspectives. There are indeed many schools of thought in finance such as financial economics, quantitative finance, computational finance, agent-based finance, continuous-time finance, financial time series analysis, game theory, econophysics, behavioral finance, empirical finance, fundamental analysis, technical analysis, and strategic analysis, etc. With respect to all these intellectual developments, in our view, finance has evolved along a natural sequence of historical stages from economic finance through quantitative finance, and has now entered the age of intelligent finance.

In the academic literature, intelligent finance as a new term and concept has been proposed by the author[1–5] and sometimes endorsed by his collaborators.[6–9] However, it must be pointed out that similar ideas, views, empirical theories as well as real-world technologies have been shared, developed, implemented and used by many academic finance scholars and researchers and most notably by many professional investors, traders, speculators, and money managers. Intelligent finance has a duality of science and engineering (including art). As a science, intelligent finance aims to understand the global financial markets as the world's most complicated social complex systems of intelligent agents — risk managers, investors, traders, speculators as well as market regulators and policy-makers. As a form of engineering and also an art, intelligent finance aims to develop consistently and nontrivially profitable trading systems that are supposed to operate in the global financial markets. Now about four years since its inception, intelligent finance has now been developed from a driving concept to a state in which a basic theory of intelligent finance has been shaped with a structure emerging with more and more clarity, consistency and stability. This paper serves to present and clarify the very basic general principles underlying the thoughts of intelligent finance, and the major components of the theory. The first four general principles are: (1) the comprehensive principle, (2) the predictive principle, (3) the dynamic principle, and (4) the strategic principle. On the basis of these principles, the four major components of intelligent finance theory are identified: I — Financial Information Fusion (FIF), II — Multilevel Process Analysis (MPA), III — Dynamic Portfolio Management (DPM), and IV — Financial Strategic Analysis (FSA). In relation to stock market investment, these four components are integrated into a general framework of information-decision-control (IDC), which we refer to as an Intelligent Dynamic Portfolio Theory (IDPT). This theory — IDPT — lifts the current dynamic portfolio theories (passive index tracking and active predictive portfolio optimization) on to a new level of comprehensiveness and capability, which integrates the predictive modeling of the bull-bear market cycle, sector rotation and portfolio optimization with a reactive trend following various strategies.

Before continuing to the following more technical sections, it must be made clear that the scope of finance for the study of intelligent finance in this author's definition is confined to the global financial markets, including market analysis, modeling, prediction, investment, trading, and speculation. We shall not touch on the realm of financial market structures, financial product innovations, market regulations and policy-making.

The remainder of the paper is organized as follows: Section 2 provides a quick tour through the evolution of modern finance theory — financial economics and financial econometrics, from which a number of unsolved problems associated with this mainstream of finance are identified. Section 3 provides a brief review of more non-mainstream finance theories including agent-based computational finance, behavioral finance, econophysics as well as computational intelligence in finance and economics; after which we shall point out how intelligent finance is different from any of them and how intelligent finance is integrating all of them. Section 4 identifies seven outstanding problems which are largely ignored in the mainstream finance literature. Section 5 presents the four general principles of intelligent finance. Section 6 describes the four major components of intelligent finance theory. Section 7 formulates the author's view of the fundamental assumptions regarding the market dynamics in a Dynamic Market Theory. Section 8 advances an Intelligent Dynamic Portfolio Theory (IDPT) for stock market investment. Section 9 concludes the paper. The Appendix provides the author's personal trading principles to showcase how to bring all these principles and components together in a real-world sensible intelligent finance trading system, if a fully-automated trading system is not yet available.

2. A Brief History of Modern Financial Theory

Modern financial theory formally started with the analytical portfolio theory of Harry Markowitz.[10] However, the stochastic process modeling of financial market prices was later on traced back to the original work of Louis Bachelier[11] in his theory of speculation. Bachelier's random walk model of financial prices did not gain much interest during the first half of the 20th century, but it was then rediscovered as the paradigm for almost all the modern theoretical constructs of continuous-time finance as well as for discrete-time financial time series models. During the mid- to later part of the 20th century, finance witnessed a revolution in the quantitative analytical modeling of financial prices and risks which all came under the umbrella of the Efficient Market Theory (EMT). Milestones well recognized by the mainstream finance and economics society include, but are not limited to, the following

- 1900, Louis Bachelier produced a dissertation "The Theory of Speculation"[11] of which a major proposition was that prices fluctuate randomly, in no apparent pattern, so that it is impossible to aspire to mathematical predictions of them.

- 1933, Alfred Cowles in his paper "Can stock market forecasters forecast?"[12] examined all of the many thousands of stock selections made by investment professionals and found no evidence of an ability to outguess the market.
- 1938, John Burr Williams in his book "The Theory of Investment Value"[13] anticipated much of modern financial theory and stressed the role of dividends as a determinant of value in an early version of the dividend discount model.
- 1934–1949, Benjamin Graham in his two books "Security Analysis"[14] and "The Intelligent Investor"[15] preached selective value investing. This methodology was further extended to value and growth investing by Warren Buffett through his superbly successful investment practices.
- 1952, Harry Markowitz in his paper "Portfolio selection"[10] put forth the principle of diversification in a convincing analytical formulation so that by holding many stocks rather than just a few, an investor could reduce his or her risk while maintaining the same overall expected return or alternatively maximize the expected return with the given level of risk tolerance.
- 1964, William F. Sharpe in his paper "Capital asset prices: A theory of market equilibrium under conditions of risk"[16] proposed the Capital Asset Pricing Model (CAPM). A direct implication of this theory is that every investor should invest in the market portfolio — holding a portfolio consisting of all existing securities in proportion to their market capitalization. The essential idea is that investors are compensated for taking necessary risks, but not for taking unnecessary risk. The market risk is inescapable, so the risk in the market portfolio is necessary. Under the CAPM, an investor whose portfolio differs from the market is playing a zero-sum game. The investor has additional risk but no additional expected return. This reasoning leads to passive investing — buy and hold the market portfolio. The combination of Markowitz's idea of diversification with Sharpe's CAPM produced a powerful solution that by holding a group of securities in a portfolio, one could eliminate the company-specific risk, leaving only the market-related risk; thus it is possible for an investor to have a portfolio of the desired risk level with respect to the market and with a higher return than the return on any individual stock. The CAPM is also referred to as the Mossin-Lintner-Treynor-Sharpe CAPM due to the independent work by John Lintner,[17] Jan Mossin,[18] and Jack Treynor.[19]
- 1965, Paul Samuelson in his paper "Proof that properly anticipated prices fluctuate randomly"[20] concluded that price changes cannot be forecasted if they are properly anticipated.
- 1968, Michael C. Jensen in his paper "The performance of mutual funds in the period of 1945–1964"[21] found that, on average, all actively managed mutual funds in the US during that period failed to outperform a broad-based market index; and that past performance does not indicate future performance. He set the precedent for denoting excess performance over the market by the symbol alpha (α).
- 1970, Eugene F. Fama in his paper "Efficient capital markets: A review of theory and empirical work"[22] defined and distinguished between three forms of market efficiency and gathered evidence for them. In the weak form of efficiency, securities

prices reflect the information available in previous securities prices, so that investors cannot use past prices to predict future prices. In the semi-strong form of efficiency, securities prices reflect all information that is publicly available, so investors cannot use publicly available information to forecast stock prices, including macroeconomic and microeconomic (company-specific fundamental) information. In the strong form of efficiency, securities prices reflect all information that is publicly or privately held, so even privately-held information cannot be used to predict stock prices.

- 1973, Fisher Black and Myron Scholes published their ground-breaking paper "The pricing of options and corporate liabilities".[23] They in fact started out by basing their option pricing formula on the foundations of the CAPM, but ended up by finding out that the price of an option did not depend on the expected return of the underlying security. Robert C. Merton who later on came up with his paper "A simple model of capital market equilibrium with incomplete information,"[24] found a more elegant derivation of the Black-Scholes formula based on a replication argument.
- 1976, Stephen Ross in his paper "The arbitrage theory of capital asset pricing"[25] proposed the main alternative to the CAPM — the Arbitrage Pricing Theory (APT). Without making many assumptions about investor behavior, the APT extended the CAPM by allowing for multiple factors — more general types of nondiversifiable risk in the economy. As the name of the theory suggests, the main argument is that there are no opportunities for excess returns at no extra risk; if there were, market participants would arbitrage them away immediately. The APT maintains that the expected excess return on any portfolio is determined by its exposure to multiple risk factors and the factor forecasts associated with those factors. As a major consequence, the APT provided the theoretical basis for developing linear models to forecast asset returns using multiple economic factors.
- 1992, Eugene F. Fama and Kenneth R. French in their paper "The cross-section of expected stock returns"[26] identified three factors, as an application of the APT, that explained 95% of the variability in stock returns. The three factors are market risk, company size or market capitalization, and the book-to-market ratio. A fourth factor — momentum — was added later on by other researchers, such as Black and Litterman,[27] to Fama-French's three factor model. This four-factor model is better at explaining mutual fund returns.

As a consequence of this mainstream of prediction-free finance models, it is intriguing to note that a paradoxical conclusion emerges: the Efficient Market Theory (EMT) started with the assumption that the market prices follow a random walk and thus cannot be predicted, but ends up with predicting price movements in anticipation of a market correction corresponding to a discrepancy between the actual market prices and their theoretical predictions from APT-type multifactor models. This paradox has been studied from a different perspective by Grossman and Stiglitz[28] in their paper "On the impossibility of informationally efficient capital markets", in which they argue that if everyone in the market believes that the market is efficient, then the market cannot be efficient because nobody would have an incentive to look for arbitrage opportunities. More recently, work on noise trading e.g. DeLong *et al.*[29] has introduced an important insight that risk-averse rational types of traders may not be able to "take over" the dynamics from less rational ones since they trade less aggressively because they are sensitive to the risk induced by the other traders.

The EMT reached its height of dominance in academic finance around the 1970s. Faith in this theory was eroded by a succession of discoveries of price predictability at long horizons[30] and at shorter horizons,[31] anomalies[32] and evidence of excess volatility of returns.[33,34] Follow-through developments in finance unconstrained by the EMT can be distinguished between two large camps: one is quantitative dynamic portfolio management which has become an integration of all the data-heavy quantitative predictive models and complex trading strategies with the discipline and accuracy that mathematics lends to the pursuit of returns and the control of risk; and the other may be better referred to as the complex finance theory including computational finance, econophysics, behavioral finance, and agent-based finance and economics.

In particular, more recent work in finance finds that stock market returns, over time periods of a year or longer, are fairly predictable with certain groups of factors such as economic, fundamental, and technical factors or other alternative ones. A book by Grinold and Kahn: "Active Portfolio Management"[35] offered some fundamental quantitative insights into active portfolio management. The first four of these insights are: (1) Active management is forecasting: consensus views lead to the benchmark. (2) The Information Ratio (IR) is the key to value-added. Here the information ratio is defined as the ratio of the annualized expected residual return to residual risk, which measures the active management opportunities, and the square of the information ratio indicates our ability to add value. (3) The fundamental law of active management is that the Information Ratio is determined by the Information Coefficient multiplied by the square root of the Information Breadth. Here the Information Coefficient is a measure of skill, defined as the correlation of forecast returns with their subsequent realizations; and the Breadth refers to the number of independent forecasts available per year. (4) Alphas — the expected residual return — must control for volatility, skill, and expectations. The latest integrations of quantitative equity portfolio management and robust portfolio optimization are provided by Chincarini and Kim[36] and Fabozzi *et al.*[37] In parallel to these pure portfolio management models and methodologies, it is important to pay enough attention to another, more general, movement on Asset and Liability Management (ALM) using discrete-time multi-stage stochastic programming as well as dynamic programming. While many parts of these mathematical optimization approaches are covered by Fabozzi *et al.*[37] the more original and systematic work is collected or summarized by Ziemba and Zenios.[38–46]

3. Computational Complex Models of Finance — Agents and Econophysics

As a bifurcation from the mainstream EMT, since the 1990s, several alternative research movements have emerged, including agent-based computational finance,[47–51] econophysics,[52–63] and computational intelligence in finance and economics.[64–66] These movements may be put under the umbrella of 'computational complex models of finance' because models in this camp are computational rather than functional, and complex rather than simplistic. Researchers of computational complex models mostly come from a non-financial or economic educational background, such as physics, computer science, mathematics and complex systems.

Researchers in this camp are typically motivated by the falsification of assumptions of the EMT such as (1) market participants are rational, (2) they all have access to all the same information, and (3) they are uniform in processing the information and making investment decisions. Nowadays with the availability of large machine-readable data sets and the computational power to analyze them, enough studies on financial market prices have been conducted, resulting in sufficient evidence that these assumptions are simply untrue. Researchers in this camp are intrigued and motivated by a large range of empirical financial puzzles — stylized facts — which remain difficult to explain using the efficient market asset pricing models. These stylized facts include, but are not limited to:

(1) The overall level of volatility and long swings around fundamentals are far beyond the allowed range of the traditional asset pricing models.
(2) The trading volume is too large, reflecting continuing disagreement between investors.
(3) Absence of simple autocorrelation: Autocorrelations of prices diminish very quickly after a short time span such as 1–6 days on daily charts and are virtually absent except for a very small time scales. This implies that there are no simple price patterns.
(4) Fat tails: The distributions of price returns exhibit heavy tails, frequently following power laws with exponents of between 2 and 5.
(5) Aggregational Gaussianity: as the time scale increases, the distribution of price returns approaches Gaussian levels.
(6) Volatility clustering: Financial markets repeatedly switch between periods of relative calm and periods of relative turmoil. While the direction of market returns is generally very hard to predict, their magnitudes are often very predictable. There is strong autocorrelation for different measures of volatility on scales of up to several weeks. This is also referred to as volatility persistence.
(7) Long memory process: Autocorrelation for some of the volatility measures decays slowly, which is sometimes interpreted as a sign of long-range dependence.
(8) Volatility is negatively correlated with the returns. In technical analysis terms, this corresponds to a class of chart patterns such as broadening tops.

9. Trading volume is correlated with volatility. Obviously investors' emotions swing with price ups and downs.
10. Asymmetry in time scales: coarse-scale measures of volatility predict fine-scale volatility better than the other way around.

Agent-Based Financial Markets:
The notion of agents plays a central role in the computational complex models. In agent-based financial markets, dynamic heterogeneity is critical. This heterogeneity is reflected in the distributions of agent wealth, risk attitudes, information conditions and investment and trading strategies. Some commonly accepted basic assumptions of agents in financial markets include (1) agents have bounded rationality; (2) agents have bounded information conditions; (3) agents have limited capital; and (4) different agents can have different capital conditions, different information conditions, different decision abilities or methodologies, different attitudes toward risk, and differences in other dimensions such as learning, discipline, or personality, etc. Financial econometrics uses analytical mathematics based on a generalization of market participants and other simplifications and idealizations. The behaviors of financial markets are modeled by quantitative variables that are usually aggregate quantities like stock prices, market indexes or interest rates. An aggregate quantity is a superposition of the decision-making processes of individual economic agents. Models using aggregate variables are not concerned with the decisions of individual agents, but focus on the net outcome of the interactions of agents as reflected in the market prices. Econometric models have the advantage of being able to deal directly with the market prices and to integrate macroeconomic factors and dynamics into the market price models. However, this kind of model lacks the bottom-up explanatory power since there is no causal path from the motives, decisions and behaviors of individual agents at the micro level through complex loops of interaction with aggregate prices at the macro level. The behavior of financial markets as observed in reality can not be fully described by such econometric models. In reality, market prices are established by all the participating investors against a large diversity of capital and information conditions, different investment goals and different decision making methodologies. The complex dynamics of these heterogeneous investors and the resulting price formation process require a dynamic system model which can simulate multiple heterogeneous agents and a virtual market. Agent-based financial market models are motivated precisely by this objective of bottom-up modeling, hoping to break through the floor from the micro level of individual agents to the macro level of market aggregates.

An agent-based model of a financial market is a dynamic system consisting of a population of interacting autonomous entities — agents representing investors with their own capital and trading strategies, and a price discovery mechanism representing a market. The state of the research on agent-based financial markets is that the agent-based models are capable of simulating and reproducing stylized facts of financial markets, such as fat tails and volatility clustering, as well as phase transitions. However, there are some undesirable drawbacks, most notably: (1) Agent-based models of financial markets are typically intractable because they come along with high degrees of freedom and complexity. As a consequence, it is neither possible to fit an agent-based model to real-world financial data, nor to generate reasonable predictions. (2) Nearly all multi-agent models reported in the current literature still use rather simplistic decision-making schemes for an agent, in comparison with the sophisticated decision processes of real investors or traders.

Econophysics:
Econophysics refers to a new fledgling field, which originated in the mid-1990s, that attempts to view and study economics, especially the economics of financial markets, from the perspective of physics, and to apply the principles of physics and in particular, statistical mechanics, to the understanding of economic problems. The name 'econophysics' as a neologism was coined by the physicist of critical phenomena H. E. Stanley, and alternative terms sometimes used include "financial physics", "phynance", or "physics of finance". As a new field of economic research, econophysics was first formally introduced into the academic community by R. N. Mantegna and H. E. Stanley.[52] The mindset of the econophysicists is characterized by some principles adopted from physics: (1) The primacy of observation: As Bouchaud and Potters[54] put it: "no theoretical model can ever supersede empirical data [in physics] ... physicists insist on a detailed comparison between 'theory' and 'experiments' (i.e. empirical results, whenever available)". To many physicists the statement that observation is supreme could sound self evident. However, in economics such a statement represents a revolution since observation is a neglected topic in economics. (2) A fundamentally analytical approach to economics: Econophysics drives the analytical approach of modern physical science to an extreme, that is to investigate one effect at a time.[67] In most natural phenomena different effects occur simultaneously. One of the main challenges of physics was to identify these effects and so study them separately. Similarly, most economic and social phenomena involve different effects, and thus one of the main tasks of the economic sciences should be to disentangle and decompose complex phenomena into simple effects. Unless one is able to estimate the impact of each factor separately, any major change in business and social conditions will invalidate the previously accepted multivariate econometric models. (3) Phase transition: Inspired by the statistical mechanics, econophysicists are strongly driven by the idea of phase transition. In the broader sense, they look for statistical mechanisms of the market to explain how the micro motives of heterogeneous agents lead to the macro behavior of market prices through the interactions of agents affected by the economic information flows. In a more specific sense, the financial agents are taken to be boundedly rational and heterogeneous. This results in models such as the Minority Games[60] showing how markets function close to criticality, magnifying the details of a phase transition between market efficiency and inefficiency and the related stylized facts.

The present paper of the author is not intended to provide a comprehensive review on the still rapidly growing literature of agent-based financial market models and econophysics. LeBaron[50] provides an overview of agent-based finance. Lux[68] and Rickles[69] provide reviews on econophysics from different perspectives of physics and philosophy.

4. Outstanding Problems in Economic and Quantitative Finance

Economic finance refers to the traditional and still largely mainstream finance which originated as a coherent part of economics, including currency, banking and financial market structures from macroeconomics, and corporate finance, accounting and insurance from microeconomics, business management and the actuarial sciences. Finance and economics are therefore inherently connected, but have now become quite different disciplines, each with its own substantially developed theoretical constructs and methodologies. It is inappropriate and even harmful to simply apply or generalize economic principles to finance problems. For example, a key idea in economics is equilibrium versus disequilibrium between demand and supply, and this is usually modeled as a negative feedback loop: more demand drives the price which attracts more supply, however, this could lead to over supply, which then drives the price to lower levels. However, in finance, a higher price of an asset in the financial market usually leads to more demands, which in turn lead to an even higher price, and this often exhibits a positive feedback loop of irrational asset pricing. Financial bubbles are far more extreme and irrational than economic inflations simply because they virtually involve purely money flows and information flows, unlike economic processes that also involve material flows. This bifurcation of finance versus economics was clarified by Prechter and Parker.[70,71]

Quantitative finance refers to the analytical modeling and analysis of virtually all financial problems using modern econometric approaches and computational techniques. However, the modern financial markets give rise to such a new type of social complex systems that econometric approaches may not be powerful enough to handle. Financial markets are so rough that not only the traditional axiomatic economics approach may not be appropriate, but also the analytical mathematical and statistical models of market aggregates may not be sufficiently powerful.

In the existing literature on economic finance and quantitative finance, by and large, we consider a few important things to still be missing (i.e. not appearing or not substantially studied):

(1) A theory of the bull-bear market cycle: Virtually all the financial models of the stock markets previously developed in the literature are context-free, meaning that the dynamic process structure of the market regime was not taken into account when a market equilibrium model was constructed. Two dominant types of existing models are discrete-time price time series models and the continuous-time stochastic differential equations. While some key stylized facts are discovered, such as volatility clustering and fat tailedness, complete theories about the underlying market dynamics are largely missing. In particular, the

bull-bear market cycle turns out to be the most significant and predictable process pattern in the seemingly random walks of the stock index or price time series.

(2) Scale space of price-time: While the fractality of financial prices has been studied by many financial mathematicians and econophysicists since Benoit Mandelbrot, virtually all the fractal models of financial time series are statistical. In correspondence with the multiple time frame technical analysis of professional traders, the academic community has yet to develop a theory about the scale space of price-time, so multiple sources of analysis information and multilevel dynamic patterns of market prices can be analyzed on proper levels of time scale. Although the notion of scale space of time is central to the communities of frequency domain analysis, wavelets, and empirical mode decomposition (EMD),[72] not many substantially successful wavelet or EMD models and applications for financial problems have been reported. On the other hand, multilevel trends, waves, cycles and seasonality are the pillars to the professional technical analysis — the Dow theory of trends,[73] the Elliot theory of waves,[74,75] and the Gann theory of price-time geometry,[76] at least.

(3) Multilevel Capital Asset Pricing Models: The financial pricing models in existence, such as the Capital Asset Pricing Models (CAPM), Arbitrage Pricing Models (APM), and the Option Pricing Models, are all defined on a single given scale of price-time. However, the market equilibrium on different time scales, such as for a period of a year, a month, a week, or a day, can be very different. Thus, multilevel models for pricing capital assets and derivatives are yet to be developed.

(4) Intrinsic dynamic portfolio theory: It is encouraging to see appearances of active or dynamic portfolio theory. However, the definition of multiple periods in the current forms of dynamic portfolio theory still corresponds to regular calendar periods. Intrinsic components such as multilevel trends, cycles and seasonality as well as intermarket dynamic patterns are not yet introduced as the foundation for dynamic portfolio construction and management.

(5) A theory of financial market ecology: While the structures and mechanisms of financial institutes and financial markets remain as core topics of research for academics, the ecology of the financial markets is largely untouched. Problems of market ecology include, but are not limited to, the dynamic evolution of market participant communities (types, groups, classes, clusters, etc.), capital food chains and information food chains in a particular market and among many interrelated markets, competitions and the coexistence of different market species, and market equilibria for different dimensions on different scales of time.

(6) A comprehensive framework to streamline information flows in financial market analysis: First of all, intelligent look-after and selection of information sources are not yet included in the loop of financial market analysis. For instance, virtually every financial model (either discrete- or continuous-time) is constructed with a predefined or given data set of a single time resolution, and there is no

intelligent zoom in or zoom out on the information sources. Secondly, we are only at the beginning of considering how to streamline information flows throughout various market analysis components — macroeconomic analysis, corporate-level fundamental analysis, technical analysis and portfolio management, etc.

(7) Comprehensive trading systems including both human and computational intelligence: Complete fully-automated trading systems without human intervention, operating in the global financial markets, are still far beyond reach for virtually all the market participants (perhaps except for a small number of powerful financial institutions who have developed their own proprietary trading systems for their selected markets). Until that goal is reached, the norm is still that a trading system must comprise both human and computational intelligence. In this long-lasting period, computational intelligence can at best serve to provide component solutions to well-defined tasks, while human intelligence must at least take care of the meta-level issues. Consequently, any complete trading system involving human and computational intelligence must still be personalized to fit the risk attitude, information conditions and capital restrictions of the trader (institution or individual). On the other hand, as long as the market is dominated by investors and traders who still rely on their human intelligence for trading decisions and their execution, the dynamic patterns, if any, must still be defined by mass psychological dynamics superimposed on economic and business fundamentals.

Academic and professional finance are inherently connected with interactions, but they have still become quite different schools of thought, each with its own substantially developed methodologies. Academic finance focuses more on financial governance and risk management, while professional finance is more concerned with profit making while keeping risk checked only as a necessary condition. It is a matter of fact that academic quantitative finance has been successful in constructing and developing market-neutral mathematical models of price volatility and returns, including modern portfolio theory, arbitrage pricing theory, option pricing theory, GARCH, and co-integration, etc. However, academic scholars have found no advantage in themselves in areas such as stock selection, the modeling of absolute directional movements in market prices, and market timing, in contrast to professional investors and traders who focus primarily on the market activity data and real-time information from both inside the markets and outside. Intelligent finance has emerged to meet the need to integrate the academic and professional knowledge and wisdom in a natural order and on a scientific basis.

5. Foundational Principles of Intelligent Finance

Aims of Intelligent Finance:

In contrast with typical quantitative finance that focuses on econometric models of financial systems and markets, intelligent finance takes the finance of a nation or the whole world as a living complex system made up of intelligent agents of all different types and sizes, and aims at developing a coherent understanding and integrated intelligent finance systems for investing, trading, banking, insurance and other financial applications. Therefore, the approaches taken by intelligent finance are more holistic, coherent, and integrative, but of course are still based on all the time-tested truthful knowledge and understanding of economic and quantitative finance. However, once we treat the global financial markets as living social complex systems, we naturally assume that a financial market can adapt or learn, so the market will react to a succession of the same kind of events with changing attitudes and magnitudes, and the market will remember things in memories of different lengths or the market will forget or ignore things after a period and then recall them again. However, because there are always old investors who leave and new investors who come in the market, all the investors as a whole still remain boundedly rational, and there are still relatively robust price process patterns reflecting the human nature of the investing public.

Intelligent finance represents an emerging comprehensive perspective of global financial markets, unifying professional empirical knowledge and wisdom and art of market analysis, investing and trading, with academic research and the science of market modeling. Intelligent finance is a quest for a comprehensive approach, methodology and system of financial market analysis, investing and trading, that aims to generate absolute positive and nontrivial returns on investment by means of exploiting the maximum information about the markets from all conceivable general perspectives, and simultaneously minimizing the very last risk — the incompleteness of a seemingly comprehensive investing or trading method or system.

Tenet of Intelligent Finance:
The key tenet of intelligent finance can be summed up by stating that every existing approach or methodology of financial market analysis, investing and trading should be considered to be a part of the total toolkit (arsenal) for profitable trading; its effectiveness is time varying relative to the state of the art of the total toolkit currently possessed by the investing public and the current market mode and situation. In this sense, intelligent finance provides a meta-level intelligence to finance in general.

Four Foundational Principles of Intelligent Finance:
Intelligent finance is constructed on the basis of four founding principles in contrast with the existing econometric quantitative finance:

(1) The Comprehensive Principle: An intelligent finance model or system must exploit all the legally available information (public and commercial) regarding the financial markets, their underlying economies and surrounding societies. We believe that the market is always in a state of swings between efficient and inefficient modes, on multiple scale levels of price-time; it is possible to go beyond the EMT to study the dynamic evolving processes of the market between

equilibrium, non-equilibrium and far-from-equilibrium states, in multiple dimensions. However, in order to do so, it is necessary to exploit all the information available. This property of intelligent finance leads to the idea of Financial Information Fusion (FIF) where the information sources are included as the starting line for the loop of the financial market analysis and investing/trading decision, implementation and execution processes.

(2) The Predictive Principle: An intelligent finance model or system must exploit all the historical patterns from the existing data and current information flows in order to project the markets and the background world into the future in scenarios with probability distribution. We believe that the world is not chaotic and that human nature tends not to change; therefore, there are robust dynamic patterns in the evolving process of market equilibrium versus non-equilibrium. Most such patterns are quite abstract, beyond common sense, and often against human nature, due to bounded rationality, limited resources, the very human nature of market participants and due to the heterogeneity of these qualities and conditions of all market participants. Fundamentally due to the persistent and/or recurrent existence of market behavioral patterns, the detection, modeling and probabilistic prediction of market price trends, cycles, and seasonality are possible, with variable economic value.

(3) The Dynamic Principle: This has three implications here: First, not only do patterns exist in the market behavior, but we also believe that most patterns are nonlinear and complex with both stochastic and dynamic natures and open to the future. Second, at any moment of time, a certain objective prediction is possible; however, if this prediction (or a similar one) is publicized with sufficient attention, it can be absorbed by the market. Furthermore, the absorption of a prediction may defy the prediction itself. Third, the reflexivity is for real: not only can the fundamentals lead the technicals (such as prices) of the market, but the technicals can also affect the fundamentals, for instance, the rising prices of a stock can improve the financial conditions of the underlying company.

(4) The Strategic Principle: we should always be aware of the limitations of mathematical and computational modeling and of the existence of strategic investors/traders who consciously know that their transactions can and will affect the market prices either due to their sheer size or due to their status in the public attention. Therefore, intelligent investors or traders should react and act on the strategic intents of strategic investors or traders.

On the basis of these foundational principles, we have formulated a few core concepts of intelligent finance as follows:

(1) Scale Space of Price-Time: A point of departure of intelligent finance from the neoclassical EMT is the recognition of a fundamental dimension — the scale space of price-time — which is missing, or never clearly spelled out, in the EMT. We believe that nothing can escape from the scale space, i.e. no pattern of

market behavior is undetectable in the scale space where we can zoom in or zoom out to see the prices on a different level of the time-price scale (physical scale) and on a different level of the price trends (intrinsic scale).

(2) Multilevel Dynamic Market Hypothesis: Financial markets are heterogeneous with participants of different conditions, typically having different time horizons of investment. The market is always in a state of swings between efficient and inefficient modes, on multiple levels of time scale. This is usually referred to as market regime switch or shift. The swing between calm and volatile periods is a manifestation of the market mode swings. This hypothesis is discussed in more depth in the next section.

(3) Multilevel Dynamic Equilibrium: Supply-demand equilibrium occurs as multiple dynamic processes on different (scale) levels of price-time. It is important to know on what level an equilibrium process is under consideration. We believe it is possible to go beyond the wall of the EMT to study the dynamic evolving processes of the market between equilibrium, non-equilibrium and far-from-equilibrium states, on multiple levels of scale or trend.

(4) Multilevel Dynamic Patterns: There are robust dynamic patterns in the dynamic equilibrium processes, most of which may be quite abstract, beyond common sense, and against human nature, due to bounded rationality, limited resources, and the very human nature of market participants.

(5) Multilevel Profitable Opportunities: It is possible to break the near-symmetry between profit and loss (as implied by the EMT) by exploiting robust dynamic patterns using intelligent trading systems. Profitable opportunities for intelligent traders exist on multiple levels of time scale. There are consistent winners in each of the investment methodologies such as pure technical traders, or long-term fundamental investors. Each type of consistent successful investor has discovered robust dynamic patterns in its domain with its characteristic time horizons and dealing frequencies or decision parameter ranges or thresholds. However, at any given moment of time the most profitable opportunity windows may be dynamically shifting in the scale space and in the ecological systems of global financial markets, such as different markets of different types or different countries.

With these core concepts in mind, we can now summarize our views of the financial market into a dynamic market theory as follows.

6. A Dynamic Market Theory

As a counterpart to the EMT underlying the econometric quantitative finance, we postulate a dynamic market theory as a basis for constructing the theoretical framework of intelligent finance. This theory consists of the following hypotheses and beliefs about how the financial markets really work.

Heterogeneous Market Hypothesis: *Market participants are not homogeneous; there are producers, risk managers (hedgers), investors, traders and speculators; different participants react to the same information in different ways with these characteristics:* (1) *different types of participants may have different goals of investment;* (2) *they may have different time horizons and dealing frequencies;* (3) *they are likely to settle for different prices and decide to execute their transactions in different situations, so they create volatility;* (4) *the market is also heterogeneous in its industrial and financial sectors and in the geographic location of the participants.*

The empirical implicit wisdom underlying this hypothesis goes back at least to the 1880s when Dow put forward his theory of trends of different significance and magnitude — primary, intermediate and minor trends, where Dow distinguished between market movers and passive investors. Explicit expressions of the heterogeneous market hypothesis as presented here were mentioned previously by financial economists and econophysicists such as Gencay *et al.*[77]

Fractal Market Hypothesis: *Different participants with different time horizons and dealing frequencies share the same human nature, and consequently the market prices exhibit a fractal structure.*

The fractal structure of financial market prices was first observed and qualitatively described by Elliott in the 1930s and then mathematically defined as fractals by Mandelbrot in the 1970s. The term "fractal market hypothesis" was then stated by Peters,[78] only referring to the existence of a fractal structure in market prices. Here we re-express this hypothesis by pointing out why the market prices exhibit a fractal structure.

Pan[4,5] recognized the dualism of swing and momentum as the key notion underlying the price dynamics and as the focus of attention of professional traders after a comprehensive study of the professional literature on technical analysis and trading strategies. The term "swingtum" was coined to refer to this dualism of swing and momentum. The idea behind swingtum is that the market price always appears to test whether the current swing on the current scale level will continue or whether the price will break a bound (upper or lower) of the current swing channel. The most astute technical traders will always pay their utmost attention to this area when such a test is about to occur. Accordingly, Pan[5] took the analysis a step beyond the heterogeneous market hypothesis and fractal market hypothesis and postulated the following hypothesis:

Swingtum Market Hypothesis: *The fractal market prices exhibit robust stochastic dynamic patterns in the scale space of price-time, which can be described in terms of multilevel trends, swings and momentums.*

According to Pan,[5] price swings are distinguished between dynamic cycles and physical cycles. The former refer to cycles with nonlinear periodicity and without the signature of physical time (calendar time), while the latter refer to cycles with linear periodicity and with the signature of physical time. Traditionally, seasonality has referred to the yearly physical cycles. However, physical cycles include all kinds of price cycles with fixed linear periodicity, such as US presidential cycles, yearly cycles (such as the January effect), monthly cycles, weekly cycles (such as the Monday or Friday effect), daily cycles and even intraday cycles. However, the importance of "swingtum" as a core concept representing the dualism of swing and momentum conceived from the professional literature has yet to be recognized by academic researchers.

Bounded Rationality and Limited Resource Hypothesis: *every market participant has bounded rationality and limited resources, and is more or less constrained by his/her human nature.*

This hypothesis is a return to the reality from the earlier rationality assumption in the traditional economic theories. The whole new area of behavioral finance is motivated by this realization. In line with these four hypotheses on market dynamics, we can summarize our beliefs about how the financial markets really work and what intelligent finance can do to make better investment decisions as follows.

Beliefs in Dynamic Markets and Intelligent Finance:

(1) The market is always in a state of swings between efficient and inefficient modes, on multiple levels of time scale;
(2) It is possible to go beyond the EMT, to study the dynamic evolving processes of the market between equilibrium, non-equilibrium and far-from-equilibrium states, in multiple dimensions;
(3) There are robust dynamic patterns in the evolving processes due to bounded rationality, limited resources and the very human nature of market participants;
(4) It is possible to break the symmetry between profit and loss by exploiting such robust dynamic patterns using a trading system.

In fact, these beliefs are shared by most econophysicists and active portfolio theoreticians and practitioners. These beliefs provide enough of a driving force for intelligent finance to take firm steps in finding out the theoretical framework of the intelligent finance theory as outlined in the next section.

7. Major Theoretical Components of Intelligent Finance

Corresponding to the four foundational principles as described in Sec. 5, the first four major components of the intelligent finance theory can be identified as follows: (1) Component I — Financial Information Fusion (FIF), corresponding to the comprehensive principle; (2) Component II — Multilevel Process Analysis (MPA), corresponding to the predictive principle; (3) Component III — Dynamic Portfolio Management (DPM), corresponding to the dynamic principle; and (4) Component IV — Financial Strategic Analysis (FSA), corresponding to the strategic principle.

Component I — Financial Information Fusion (FIF):
Virtually all finance theoreticians except the steadfast EMT believers would agree that it is always advantageous to exploit as many sources of information that may drive, affect or influence the target market as possible. There is, however, no systematic investigation on what the relevant information sources are, how to detect them or to measure how relevant they are, and, subsequently, how to streamline the information flows from these sources through the information-decision-control (IDC) process loop of financial market analysis, investing and trading. Financial Information Fusion (FIF) is exactly a functional component of intelligent finance to perform these tasks on a continuous time basis.

Information fusion has emerged since the mid 1990s, first of all, as the core functional component of the C^3I systems (Command, Communication, Control and Information), which originated in the defense information science and technology. The present author chaired the 1997 International Workshop on Image Analysis and Information Fusion[79] and served as a committee member for the first International Conference on Information Fusion (1998), which marked the formal establishment of the International Society of Information Fusion (ISIF). In a sense, we are inspired by the defense information fusion theories and methodologies, and we believe there is a good opportunity and good value in establishing the theory of Financial Information Fusion (FIF), although we do not agree that we should simplistically compare the financial markets with the battlefields.

The utmost objective of FIF is to form and maintain a big picture of the target market through fusing all the incoming information flows stemming from all the relevant information sources. In order to achieve this objective, FIF has the following tasks to accomplish or manage:

(1) Identification of information sources relevant to the target market. These sources may include: global, national or regional macroeconomic indicators; global, international or national financial market indexes or prices; microeconomic indicators, including corporate finance ratios; news and events from inside or outside the market of different influence magnitude or dimensions; and strategic intelligence information about substantial market players, market regulators, and other agents of influence.
(2) Mapping out the information flow paths throughout the process loop of financial market analysis, investment decision and trading execution. For example, a typical waterfall prototype is market selection — trend prediction — portfolio optimization — technical trading, where there must be multiple feedback loops.
(3) Modeling of information flow fusion. This deals with how to extract, derive or infer new downstream information from the upper-stream information flows. For example, the prediction of asset returns requires models with multiple factors — economic, fundamental and technical — as inputs; these kinds of modes should in general be highly nonlinear and dynamic. In general, models of information

flow fusion can be probabilistic such as dynamic Bayesian networks or Markov chains, nonlinear pattern recognition models such as multilayer feedforward or recurrent neural networks, stochastic dynamic systems such as stochastic differential equations, neural fuzzy computational intelligence, chaos-theoretical nearest neighbor clustering and classifiers, and rule-based systems.

(4) Restructuring and optimization of information source selection, information flow charting and inference modeling. There must be iterative loops among the first three tasks as described above, which involves reselection of information sources, restructuring of the information flow paths and junctures of inference, as well as optimization of the model structures and parameters.

More in-depth discussions on the FIF component are provided in a companion paper of this paper.[80]

Component II — Multilevel Process Analysis (MPA):
Under the Heterogeneous Market Hypothesis (HMH), it is now commonly accepted that the foremost characteristic distinguishing between different categories or clusters of market participants is their time horizons and dealing frequencies of investment or trading, which may be recast into the notion of multiple levels of price processes. Here the notion of "level" may refer to the characteristic scale of time or characteristic trend. In general, we can assume that there are multilevel processes going on that altogether make up the unique historical price time series. The objective of Multilevel Process Analysis (MPA) is to decompose the given historical price time series into multilevel processes, where each single-level process corresponds to a self-coherent trend-swing process and all the single-level processes are mutually distinctive. Here a trend-swing process refers to a self-contained trend followed by its reversal and so forth, in which we can clearly see the swings and each monodirectional trend corresponds to a segment of the swing process.

It would be desirable if we could reconstruct the multilevel trend-swings, multilevel dynamic cycles and physical cycles. Dynamic cycles are those price swings with a nonlinear phase dynamics such as financial bubbling processes modeled by log-periodic power laws or observed empirically as Elliott waves. Physical cycles are those price swings with linear phase dynamics such as seasonalities on a yearly, monthly, weekly or daily basis, or even intraday hourly basis. Business cycles are dynamic cycles; but the presidential election cycles for the US and other countries are close to physical cycles.

There are several approaches for decomposing a given financial time series into multilevel processes, including top-down time series generalization which is a recursive splitting process, multilevel zigzag extraction which is a technical indicator with a retracing ratio, wavelet transforms, and Empirical Mode Decomposition (EMD) (also called the Hilbert-Huang transform).[72]

There are many facets of usefulness of the MPA, including (1) Registration of multiple factors of influence on price processes of proper levels, for example, people's weekly life style — weekly biological rhythms — may only be significant in short-term daily price processes, but it certainly should be ignored for long-term investment; (2) Modeling and prediction of single-level trend-swing processes should then only use the proper information from the given level and neighboring upper and lower levels; and (3) Modeling and prediction of cross-level trend-swing processes should then be possible and useful, for example for investigating how a big impact from outside will affect the market prices on multiple levels of time scale, magnitude, and trend-swings.

In particular, for the probabilistic prediction of the price trend-swings at one step forward or at multiple steps, nonlinear and/or nonparametric models can be constructed in terms of explicitly defined multilevel process information. More detailed discussions on the MPA component are given in Ref. 81.

Component III — Dynamic Portfolio Management (DPM):
In line with the dynamic principle, there should be a component on Dynamic Portfolio Management (DPM). Modern Portfolio Theory (MPT) that started with Markowitz[10] is the first milestone of the modern financial theory (MFT) which marked the transcendence of financial investment from empirical and qualitative thoughts and methodologies to a quantitative discipline of science. Since then and up to now, MPT has evolved through three major stages corresponding to different approaches in portfolio construction and optimization: single-period static portfolio theory, passive dynamic portfolio theory (index tracking) and active dynamic portfolio theory.

Single-Period Static Portfolio Theory: Markowitz's original theory of Mean-Variance Analysis (MVA) is a static portfolio theory, implying a single time period, and all the future dividends are discounted into an expected return on investment. Only statistical moments of the distributions of the historical return data are taken into account, and the very nature of the time aspect of the return history is lost.

Passive Dynamic Portfolio Theory: The first step toward lifting the portfolio theory from a static to dynamic theory was in fact taken by Sharpe[16] with his Capital Asset Pricing Model (CAPM). Based on Tobin's idea[82] of a single super-effective portfolio of risky stocks and the riskless asset for the whole market, the CAPM holds that the market portfolio should consist of all risky stocks with shares defined by a ratio of their market capitalization to the capitalization of the entire market. Consequently, according to the CAPM, the average return on a stock relative to the whole market can be determined by the ratio between the covariance of this stock return and the overall market return, scaled by the variance of the market return. This model can naturally serve as a basis for an investment strategy: if the return on a stock is lower than that predicted by the CAPM, one should buy it and hold the position until the market corrects the mispricing. However, since everyone will try to do the same, the supply-demand mechanism should make the returns on all these riskless portfolios equal to the riskless interest rate. This idea was expressed by Ross[25] in the Arbitrage Pricing Theory (APT).

Both the CAPM and APT are consistent with the EMT, implying that in the long run it is impossible to maintain a return on investment higher than the market index. This line of portfolio theory from the EMT, through the MVA, CAPM and APT has become the dominant approach for passive dynamic portfolio management, which is famously called Index Tracking. In fact, it has been reported by tracking most of the mutual funds in the US throughout the last three decades that the majority of the funds have not outperformed the market index.

Active Dynamic Portfolio Theory: The APT extended the CAPM by allowing multiple factors representing more general types of nondiversifiable risk in the economy. The underlying main argument is that there are no opportunities for excess returns at no extra risk; if there were, market participants would arbitrage them away immediately. Conversely, an investment's expected return can be determined from its exposure to multiple factors. Most of the follow-up developments on (linear) dynamic portfolio theory were extensions of the APT through testing various risk factors. However, the biggest limitation of the APT is that the factor risk premiums are supposed to be constant. Researchers such as Ferson and Harvey,[83] soon considered that the risk premiums might not be constant over time. The model parameters may need to change with time in response to a set of exogenous variables.

Active portfolio management takes the view that the market is not always efficient. There are inefficiencies such as market anomalies appearing intermittently. It is possible to choose stocks that will outperform a market index. Active managers sometimes aim for absolute positive returns without any reference to a market index or benchmark. Grinold and Kahn[35] proposed the fundamental law of active management, stating that the information ratio is the product of the information coefficient and the square root of the breadth. The fundamental law is for understanding quantitative portfolio management, highlighting the central role of forecasting. For actually doing active management, Chincarini and Kim[36] provide a clear roadmap for constructing multifactor models and forecasting factor premiums and exposures as well as stock screening and ranking. Fabozzi *et al.*[37] provide guidelines for a practical treatment of the portfolio management, translating complex concepts into real-world applications for robust return forecasting and asset allocation optimization.

The camp of active portfolio managers share the same belief in that the selection of assets of different types for strategic portfolio construction and optimization of the asset weights in a pre-constructed portfolio should be dynamic in discrete-time periods. Although continuous-time portfolio adjustment is appealing in theory, it is impractical due to at least the transaction cost. However it has to be pointed out that until recently virtually all the multifactor models for predicting asset returns in the portfolio optimization process have been linear or low-order nonlinear, in which multilevel trend-swings, multilevel dynamic cycles and multilevel seasonalities are not taken into account in the prediction and optimization processes. As a contribution from the perspective of intelligent finance, the DPM component brings these dynamic structures — multilevel trend-swings, cycles and seasonalities — into the prediction and optimization processes of the DPT.

There are two distinctive approaches to DPM: one may be better referred to as "Direct Dynamic Portfolio Management" (DDPM), and the other as "Multi-Period Dynamic Portfolio Management" (MPDPM). DDPM formulates the asset allocations directly as linear functions of exogenous factors, avoiding the problem of building a consistent set of return expectations based on the factors required in the consistency of the covariance terms of a correlation matrix. The MPDPM moves into conditional multi-period portfolio optimization under assumptions that the asset returns for each period of the horizon are not constant but vary conditionally with a set of exogenous factors in accordance with some model, and there may be budget constraints within one time period. It uses either stochastic programming or dynamic programming for determining the optimal weights. Obviously DDPM is myopic while MPDPM is more forward looking. However, because DDPM uses a moving window of history to predict the next period, it is still highly effective.

In our toolkits, there is a probabilistic prediction model called the "Probability Ensemble of Neural Networks" (PENN).[5] Unlike the other averaging ensemble of neural networks, PENN is able to generate a probability distribution of the predicted variable from the predefined predictor variable vector. Thus, PENN is useful to provide a nonlinear probabilistic prediction model to be included in the one-step DDPM or in the multi-step MPDPM. Apart from PENN, situation-based scenario matching and kernel regression in the sense of chaos theory and nearest neighbor classifiers can provide another class of powerful prediction models for dynamic portfolio theory and management.

Component IV — Financial Strategic Analysis (FSA):
We believe there is a limit that objective financial mathematics and econophysics may not go beyond, that is the proactive strategic intents of strategic investors, typically the collective minority of active hedge funds who constantly pursue absolute returns independent of the market benchmark indexes. The fundamental reason why real finance is partly considered to be an integrated intelligence is because trading in financial markets is actually a multi-agent game among traders and will remain as a big game among traders and intelligent electronic trading systems superimposed upon longer-term investment activities. Therefore, every existing part of the objective, scientific, mathematical or empirical knowledge and techniques should be treated as a component of the entire toolkit (or arsenal) for profitable trading; its effectiveness is time-varying relative to the state of the art of the total toolkit currently possessed by the investing public and to the current market mode (regime) and situation. Nowadays, computational finance focuses on developing intelligent agent models of conscious investors, traders and active speculators and consequently this kind of modeling can be generalized to simulate the ensemble

behavior of the market as a whole. However, the level of sophistication and complexity of trading agent models is still very low in comparison with strategic traders who can command capitals of significant size. Financial Strategic Analysis (FSA) is a component of intelligent finance to deal with the strategic domain of strategic investors and traders on top of fundamental analysis and technical analysis of financial markets.

In stock markets, FSA analyzes and tracks the policy changes of market regulators or upper-stream agents of influence (such as the Federal Reserve Bank for the USA or the Securities Market Regulatory Commission for China), money flow sources and destinations, and the situation and intent of the market makers in a hierarchy from the level of the market as a whole, through the level of industrial sectors and that of strong versus weak stock groups, and finally to the level of individual stocks. Through this kind of analysis and tracking, FSA is supposed to lead to selecting the most profitable markets, capturing the best timing of entry opportunities, optimizing the positions and portfolios, and deciding the good timing of exit from the market, while taking advantage of the resulting strategic analysis information.

The actual tasks of FSA include, but are not limited to, the following: (1) tracking and analyzing the decision making processes and policy changes of the market regulating agencies; (2) tracking and analyzing the strategic and quantitative portfolios and strategic intent of institutional or big investors of relevant scale in the given market, the portfolios and strategic intents of the market makers; and (3) tracking and analyzing the position and portfolio distributions of other investors of lesser size and their behavioral patterns. The information sources for FSA include: public information like price data, fundamental information and news; transaction records available from stock exchanges and brokers and market statistics; and other non-public but commercial information about major stockholders of each listed company, the strategic intent of market makers; as well as corporate plans or pre-press news. Public information is freely available, but other non-public information should come at a price, but still be legally purchasable.

8. An Intelligent Dynamic Portfolio Theory (IDPT)

The four major components of intelligent finance, namely, Financial Information Fusion (FIF), Multilevel Process Analysis (MPA), Dynamic Portfolio Management (DPM) and Financial Strategic Analysis (FSA), need to be integrated into a coherent framework of information-decision-control (IDC) for any well-targeted and well-defined financial investment applications. In stock markets, here we advance a specialized form of this framework — an Intelligent Dynamic Portfolio Theory (IDPT), as a fundamental lifting of the modern portfolio theory from the static mean-variance analysis through passive index tracking and active predictive optimization to a new level of comprehensiveness and absolute returns. The details of this theory — IDPT — will be provided in a technical paper,[84] so the description here will be brief.

Shortcomings and Open Problems with Current Dynamic Portfolio Theory:
The current developments of Dynamic Portfolio Theory are still consistent with the EMT, but are constrained by several severe shortcomings and open problems needing to be solved:

(1) The multifactor models for predicting asset returns are defined with macroeconomic or fundamental factors, but the shortest interval (frequency) for taking an observation of such factors is monthly. However, it is a matter of fact that the monthly time basis is too coarse for reacting to financial market risks such as market crashes, large or small. In principle, we need multiple levels of time scale, including monthly, weekly, or daily levels at least, if not considering the intraday time frames.
(2) For stock portfolios, the dynamic process structures of bull-bear market cycles, multilevel trends, waves, and cycles should be taken into account. These aspects are currently ignored in the prediction models of asset returns and in the pure statistical correlations in the portfolio optimization.
(3) For stock portfolios, the stochastic and dynamic process structures of sector co-movement and sector rotation are currently ignored. Although the moment is treated in the Black-Litterman's asset allocation model,[85] the financial market context for this model is impartial, without a big picture of a bull-bear market cycle.
(4) The current models of Dynamic Portfolio Theory depend on the predictive capability and quality of the multifactor models for asset returns. However, it is known by professional investors and traders that the market is not always predictable irrespective of whether exogenous economic or fundamental factors or using endogenous technical factors are used. Trend following reactive trading strategies are ignored in the literature on portfolio management.

Identification of these shortcomings and open problems provides some of the major motivations to our development of the Intelligent Dynamic Portfolio Theory (IDPT).

Key Points of the Intelligent Dynamic Portfolio Theory (IDPT):
The new theory — IDPT — aims to lift the current dynamic theory of portfolio management from purely predictive models using exogenous economic and/or fundamental factors to the new level of comprehensiveness and completeness by integrating predictive models of asset returns or portfolio optimization with dynamic process models of market indexes and prices on multiple levels of time scale as well as reactive trading strategies for real-time portfolio management. The theory — IDPT — is characterized by the following fundamental insights about the market reality and our corresponding considerations and strategies:

(1) Along the time line of the historical stock index movement over more than a hundred years, the Bull-Bear Market Cycles (BBMC) provide the most reliable

dynamic process contexts for stock market modeling. Starting with Bachelier,[11] stock market indexes or prices have been modeled as random walks. However, the BBMC are the farthest from random walks, exhibiting strong dynamic process structures that are traditionally observed as Dow trends, Elliott waves, or Gann cycles empirically, and recently modeled as financial bubbles and anti-bubbles in the form of Log-Periodic Power Laws Sornette *et al.*,[56,86,87] or other statistical or mathematical models. The BBMC also corresponds to the business cycles studied in macroeconomics, and there is a phase shift between the stock market cycles and business cycles.

(2) Market models for stock portfolio management must be context-dependent, and so the bear-bull market reversal, trends, waves and cycles as the structures of a market regime context must be taken into account. Virtually all the technical indicators and chart patterns studied in technical analysis and the context-free time series models studied in financial econometrics fall short of reliability and well-definedness due to their lack of a market regime context.

(3) The dynamic processes of market indexes or prices to be modeled must be defined on multiple levels of time scale to reflect the multilevel trends, waves and cycles. Accordingly, the portfolio construction and optimization must be treated on the multilevel time bases, so the market risks or stock-specific risks on all levels of time scales can be managed on their proper time scales.

(4) For stock markets, the stock selection must be included into the loop of information-decision-control (IDC). In particular, the first principle should be to focus on the leading stocks in the leading sectors (and in the leading stock markets, if global macro investment is considered). Leading sectors are the strongest sectors in a stock market. However, leading or lagging sectors can change during a bull market or a bear one. This is the so-called notion of sector rotation.

(5) We recognize and accept the market reality that the market is not always predictable using any factors — economic, fundamental or technical, and there are always uncertainties in the market. Accordingly, we must include reactive trading strategies along the line of trend following to fill in the vacuum left by active management using predictive modeling and optimization.

It is an obvious fact that when the stock market as a whole is falling, the sectors tend to co-move downwards; and when the market index starts turning up from a low, the sectors tend to rotate, meaning that there are always one, two or three sectors leading the upward reversal ahead of other sectors. The leaders for this new upward wave may not be the same as those for the previous upward wave. It is here that the sector rotation comes in. In the academic literature, sector rotation is a topic largely ignored. For the investment professionals, there are two complementary approaches for predicting and capturing the sector rotation: fundamental and technical. The fundamental approaches track the sectors whose profit levels increase and accelerate and whose valuations are still low relative to other sectors. The technical approaches focus on the sectors whose index returns grow faster than those of other sectors. Ideally, a complete approach for modeling the sector rotation should combine both the fundamental and technical conditions.

A preliminary implementation of the theory — IDPT — has been tested on the Chinese stock market using the daily data between June 2005 and April 2008. This period includes a big bull market between June 2005 and October 2007 followed by a severe bear market until the end of the period. The portfolio strategy is to focus on the leading sectors throughout sector rotations. Each selected sector index is traded through a trend following strategy equipped with a set of rules for entry, stop loss exit, and re-entry. The performance of the whole system is measured with the total equity return curve. For that period, the system has returned about 800% while the market index has returned about 250%, including the bull market and the bear one. Apart from the numerical results, the system performance has confirmed the attainment of two major objectives: outperforming the market index during bull markets and maintaining absolute positive returns during bear markets. More details of the theory — IDPT — and real-data test will be reported in a follow-up paper.[84]

9. Conclusions

This paper presents the foundational concepts, principles and major components of intelligent finance as a new era of modern finance theory out of a 100-year history of investing, trading, observation, understanding, theorization and research. Intelligent finance provides a comprehensive approach to break through the wall of the EMT to study the multilevel swing processes of market equilibrium. The theory of intelligent finance is firmly based on the belief that investors are neither fully rational nor chaotic, so there are invariant patterns, though maybe highly abstract and deeply hidden, in the market price behaviors, and embedded in the economic dynamics. Financial Information Fusion (FIF) and Multilevel Process Analysis (MPA) make it possible to break the near-symmetry between profit and loss on multiple time frames. Dynamic Portfolio Management (DPM) provides a natural way to realize this possibility through a complete operational loop which can be automated. With or without highly automated investing and trading systems, human investors and traders must remain strategically conscious with Financial Strategic Analysis (FSA) in order to survive and thrive in the market. Intelligent finance in general is still at its early stages of research and development, and much remains to be done.

Appendix: Pan Swingtum Principles

These principles as a whole form a personalized trading system of the present author. The system is named ‘Swingtum’ since it refer to the dualism of swing and momentum which is found to be the constant focus of professional traders. Virtually every time when a professional trader looks for profitable opportunities in trading, he/she has a dualism of two opposite hypotheses: one is that the price may continue along the projection of the current swing, and the alternative hypothesis is that the price may break the upper bound or the lower one of the current swing, driven by a new emerging momentum. This dualism of swing and momentum may seem quite abstract to some academic researchers who do not have first-hand market trading experience, but professional traders either know it very well or can quickly appreciate its importance even if they do not know it consciously. Here are the principles:

(1) Survival of the Fittest
(2) Enter Your Zone of Freedom
(3) Avoid the Markets to Your Disadvantage
(4) Be Practical
(5) Be Empirical
(6) Keep It Simple
(7) Trade Carefree
(8) Only Trade High-Probability Events
(9) Invest First, Investigate Later
(10) Exit First, Analyze Later
(11) Concentrate with Minimal Diversification
(12) Ride Reflexivity Process Consciously
(13) Use Leverage Judiciously
(14) Follow your System Religiously

The first seven principles are for expert traders who want to survive in the market and to win consistently, while the second seven are for master traders who want to outperform most of the consistent winners and win big sometimes. The reason for providing these trading principles here is to showcase what a personalized trading system looks like in case a complete automated trading system is not yet available. One must have such a trading system to attune one's mental decision processes and psychological processes into a winning state. Such a judgmental trading system is also indispensable for guiding the development process of a computational intelligent trading system.

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