Neuroeconomics and the Decision-Making Process

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Chapter 10
Plasticity and Memory in the Financial Markets

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ABSTRACT

The chapter questions the applicability of the Efficient Market Hypothesis (EMH) for analysis of financial markets. The overall goal is to analyze methods of forecasting future prices of financial assets based on the concept of the fractal market structure and long-term memory of past prices. Fractals in the financial markets are interpreted either as investors with different investment horizons or as a configuration of the price movement on chart. This chapter examines the fractal structure of financial markets, nonlinear methods of analysis of financial markets, plasticity and long-term memory to long-term investment horizons of financial markets, fractal analysis of financial markets, new approaches to forecast prices of financial assets, which eliminate shortcomings of the linear paradigm.

INTRODUCTION

This chapter discusses applicability of the Efficient Market Hypothesis (EMH) for the analysis of financial markets. The overall goal is to analyze methods of forecasting future prices of financial assets based on the concept of the fractal market structure and long-term memory of past prices. Fractals in the financial markets can be interpreted either as investors with different investment horizons or as a configuration of the price movement on the chart.

The need to explore the EMH is initiated by the idea that traditional analytical methods used in practice and in academia are based on the linear paradigm and exclude the fractal structure of the market. This paradigm postulates that in the situation of external influences' absence, any system, including markets, seeks balance: demand equals supply, everything is stable, and trends do not appear accidentally. Linear theory is based on the proposition that markets have no memory: news is announced then markets react and forget immediately. However, this theory does not match our every-day reality of the financial markets.

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On the contrary, recent research confirms ineffectiveness of the financial markets. This inefficiency is verified by existence of the so-called market anomalies "calendar anomalies", "price anomalies", "effect size", "effect of the news", and so forth. Such anomalies indicate the long-term memory existing in the financial markets. In these circumstances, the hypothesis of the Fractal Market Hypothesis (FMH) has been reassessed and used as the background of the analysis for the chapter.

Interestingly, on the border between the conflicts of opposing forces, one can find not nascent chaotic, disordered structures, but instead a spontaneous rise of the higher level self-organization. Moreover, the structure of such self-organization is of new kind, irrelevant to the older Newton scheme. As soon as markets have a long-term memory at the long-term investment horizons, the past behavior of price influences its future value. The intrigue lies in the fact that if the assumption of random movement in prices in the capital markets is incorrect, most of the current theories, empirical research, and methodological approaches are rendered useless. New methods must displace older methods which do not involve independence of variables and normality distribution of variables. These new methods should include fractals and nonlinear dynamics which are being applicable to real data and demonstrate greater efficiency.

Within the theory of markets, the nonlinear paradigm includes the concept of long-term memory: events that may affect the markets for a long time, and perhaps infinitely. The modern linear paradigm allows only the possibility of short-term memory, in the best case, in submartingal form. Inability of a linear system is due to the fact that the statistical deterministic systems allow a small degree of freedom. This fact significantly limits their ability to adapt; they are forced to give way to competitors in the development.

This chapter will attempt to answer the following issues:

- Fractal structure of financial markets
- Nonlinear methods of analysis of financial markets
- Plasticity and long-term memory to long-term investment horizons of financial markets
- Fractal analysis of financial markets
- New approaches to forecast prices of financial assets which eliminate shortcomings of the linear paradigm

Therefore, the practical significance lies in the intention to equip academics and practitioners with new methods and tools for analysis and forecasting future development and dynamic of the financial markets.

THEORETICAL FRAMEWORK

Analysis of the key theoretical concepts explaining financial market behavior should begin with the founding father of the traditional theory of market, Loui Bachelier (1964). In 1900 he attempted to defend his doctorate thesis titled, *Theory of Speculation*, in which the basic question of price development was articulated. Most approaches of that time centered on the simple cause-answer scheme: if an event happens, prices react with a definite and expected result. Such connection could be easily observed after an event, but could hardly be predicted in advance. Bachelier has chosen another way to explain this phenomenon by attempting to apply theory probability to financial market development and to estimate the probability of price instability via a set of factors. He discovered existing analogy between heat dispersion within a substance (or Brownian movement of molecules in water) and fluctuation of bonds costs.

By comparing them, he demonstrated that diagramming monthly or annual fluctuations created the so-called Gaussian curve. In the centre of the curve, a large number of small changes is grouped around while a few of big changes are spread on edges. Bachelier used the Brownian movement description to create an analogous equalization for probability of price fluctuations. The risk of buying bonds was considered a standard deflection in the Gaussian curve.

This theory was applied in practice when Bachelier calculated the profit probability for a buyer of a 45-day call (with a mistake of one percent). Although by 1900 several books about financial markets had already been published, this sphere of economics was not considered a research field. Therefore, Bachelier did not earn his doctorate degree; however, some 50 years later his dissertation was discovered, and on its foundation the theory of markets, investment, and finance was created. Harry Max Markowitz (1952) used Bachelier's results to create a theory of portfolio. The idea was as follows: If there are two portfolios of investments, the variant with the maximum expected average profitability and minimal dispersion (risk) must be chosen.

For calculation of the average mean value, the expected profit for each type of stocks in a portfolio is multiplied with the weight coefficient. The dispersion is calculated using correlation activities between stocks. On the base of this theory, the follower of Markowitz William Sharp developed the Capital Active Pricing Model (CAPM) to help calculate the threshold value of the expected delivery enclosure of investments and to make a decision (Sharp, 1964).

In the 1970s when the new type of market was born (the market of calls), Black and Scholes (1973) moved further toward classic financial theory and created a Equation for the calculation of call cost. Today, this Equation (with some corrections) is used by corporate financiers while buying unexpected risk insurance. In the same period, Fama (1976) established the law of the Brownian movement in financial markets. He Equationted the hypothesis of the effective market and demonstrated the correlation between effective market activities and Brownian movement. The hypothesis came from the idea that in the ideal market, the securities cost completely reflect information, which could predict future events. In financial markets, the number of buyers is equal to the number of sellers. In such circumstances, both buyer and seller agree upon a price referred to as "the right price". To extend this idea to the fund market as a whole, one can conclude the common market price also should be "right".

In other words, considering available information the published stock price should reflect the best common market of future profit. However, following the fund market crisis of 1987, which did not comply with the standard model of financial risk, the new method Value at Risk (VaR) was established. In the beginning it was used by a group of financial institutions in the USA, and only in 1994 was this method openly published by financiers of JPMorgan Chase & Company. In 1997, this method appeared in the field of vision of state institutions in Europe and the USA which were responsible for regulation and control over financial activities. For a state, it was extremely convenient instrument to control market risks in trade portfolios banks, investment, and insurance companies.

Therefore, this method has spread among financial institutions throughout the world. The method called Expected Shortfall or Conditional Value at Risk (CVaR) was first employed in the beginning of the 2000s as an alternative to the VaR method. It was linked with the fact that the popular VaR has some shortcomings. The core shortcoming is underestimation of risks in case, if waste distribution has so called "heavy tails". Heavy-tailed distribution means probability distribution which tails are not exponentially bounded. Synonimous terms are the fat-tailed, the long-tailed distributions, and together with the heavy-tailed distributions are used to describe the subexponential distributions. The Shortfall is a more conservative risk measure than the VaR. For the same level of probability, this method demands to reserve greater capital, but at the same time this measure can more accurately estimate risks in case of "heavy tails".

Today, the methods for the analysis and prediction of financial market behavior are borrowed from neuroeconomics and have become extremely popular. Many economists believe neuroeconomics as an interdisciplinary field in its broadest sense is a neurobiology of decision-making (decision neuroscience) (Glimcher & Rustichini, 2004; Rilling et al., 2008). It combines neuroscience, economics, psychology, and other disciplines to form the basis of new knowledge about mechanisms of decision-making and helps to simulate the behavior of humans and animals.

It is important to note that neuroeconomics focuses on the study of the neurobiological mechanisms of the simplest (perceptual) solutions, as well as on the nature of irrationality on causes of stronger emotional response to a loss than to acquisition (loss aversion) (Tom et al., 2007). Temporal discounting has been intensively studied; namely, the causes of disproportional preference of momentary interest in comparison with interest in deferred time (McClure et al., 2004). For the research of financial market memory, the most interesting is the study of brain mechanisms determining subjective utility in the selection process of possible alternatives, the search for an answer of how the human brain considers risks when making financial decisions. This aspect also links with consumer behavior (Knutson et al., 2005; Kuhnen & Knutson, 2005); namely, the perception of price and advertising (Klucharev et al., 2011; Plassmann et al., 2008).

RESEARCH QUESTION

The irrational behavior of investors which does not fit into traditional regulatory economic theory is the result of evolutionary selection embodied in the structure and function of neural nets of the brain. This irrational behavior is expressed in the so-called market anomalies. In turn, market anomalies confirm existence of the fractal structure of financial markets and a long-term memory. In neuroeconomic theory, the greatest potential in terms of applicability to the financial markets analysis is in the Fractal Market Hypothesis (FMH). In the FMH framework, financial markets may be considered an analogue of neural brain networks, and fractals (investors with different investment horizons) as an analogue of neurons.

To assume that investment decisions can be predicted on the basis of analysis of the information impact on various neurons (fractals), the disclosure of relevant neural mechanisms opens new horizons in understanding the nature of the investors' behavior in financial markets. For this reason, market anomalies should the subject of further consideration on the basis of comparative analysis of the FMH and classical Efficient Market Hypothesis (EMH) as mentioned in the Introduction.

METHODOLOGY

The applicability of basic assumptions of the EMH model and normality of distribution of price changes in financial markets should first be questioned. EMH researchers interested in fund markets discovered a number of anomalies, thus giving rise to some doubts about the assumptions of normality. One such anomalie was discovered in 1964 by Osborne in his study of the density function of profits in the stock market; namely, the tails of this function are thicker than a size of normally distributed value. However, Osborne did not pay any attention to this issue.

Fama (1965) discovered while studying daily profits that profits have a negative asymmetry: the greater number of observations was concentrated in the left tail than in the right. Moreover, tails of distribution are thicker and the peak of average value is much higher than predicted by normal distribution. This fact was later verified by other research. For instance, in 1997 the Dow-Jones index during the same day fell by 7.7% with the lowest probability. In July, 2002, the index fell three times in seven days with the lowest probability. On October 19, 1987, the index fell by 29.2% which was the worst trading day in the 20th century. According to the standard model of financial theory, such an event could occur in less than one event per 10^{50}.

The applicability of the EMH should also be examined. Following Fama's publications, much research was devoted to fortuity of movements in share prices on the stock market in order to demonstrate efficiency of the capital market. Contrarily, recent research confirms inefficiency of different capital markets by discovery of so-called market anomalies. Basic anomalies on fund markets can be divided into following types:

1. **Calendar Anomalies:** These are effects influencing the anomaly of price behavior and being dependent on timely, calendar, and seasonal factors. Typical calendar anomalies are effect of month, effect of a weekday, effect of pre-holidays and holidays, effect of weekends, effect of the New Year, mid-month effect, mid-day effect, full moon effect, and seasonal effect. Calendar anomalies are revealed not only in fund markets, but also on resource, monetary markets, etc. Some of them are about degeneration, but some are sustainable. The brightest and frequently pronounced is "the effect of January": during at least the past 70 years, an excess of the average stock returns in January over their profitability in other months has been observed. On the New York Stock Exchange, the size of excess is about three percentage points. In the last 25 years, this stock exchange also demonstrates "the week day effect": namely, on Mondays dividend yield almost always has a negative value. For instance, the Russian stock market demonstrates that trading sessions on Monday start with "sagging", which confirms the presence of "the beginning of the week effect" on the Russian stock market.
2. **The Size Effect:** It is considered that small-cap stocks tend to behave better than the larger stocks with the same risk indicators. One of such research follows this anomaly during the period 1926-1980. Based on the size of the companies listed on market, all stocks were divided into quintiles. The quantile with the smallest capitalization yield exceeds the yield in other quintiles, as well as the indices yield. This effect became very popular in press and academic journals, such as the *Journal of Financial Economics*. The company Dimensional Fund Advisors (DFA) provided a research of the stock portfolio of small-cap companies and found abnormally high returns that differ from predicted by the model CAPM. But after publication of the results abnormally high (due to "the size effect") revenues in the US market gradually began to decrease, and more recent studies have recorded statistically insignificant or significantly smaller revenues compared with the period 1926-1980s.
3. **Price Anomalies:** Trade ideas, based on price anomalies, are one of the most widespread. There are a lot of confirmations of the fact that investors often overestimate growth prospects of companies or underestimate the market value of companies. It occurs because pricing strategies bring higher revenues due to mistakes of typical investor, and not because they are potentially more risky. There are at least two well-known examples of price anomalies. The first one is low coefficient P/B (Price/ Balance sheet profit). The research of this phenomenon embraced almost all stocks at

> NYSE, AMEX and NASDAQ during the period 1963 – 1990s. Stocks were divided into 10 groups using the coefficient P/B and have been ranged. It was discovered that income securities with the worst P / B superior income securities with the best P / B in each decile by 8% to 21.4%. The second example as low coefficient P/E (Price/Yield) demonstrates that stocks with a low P / E have an increased yield in comparison with a high P / E stocks. Some research on this matter has been conducted on the USA bond market.

The share prices of various companies from 1973 to 1993 were analyzed. These shares were divided into quintile, based on indicators of the P / E, and profitability for each group compared with the average. It was found that the profitability of the group with the lowest P / E significantly exceeds average results of the year and the quarter in particular. Moreover, the increased yield was detected for securities on which the release of positive corporate news was distributed, as well as for securities with negative releases. It means that any news, positive or negative, will impact positively on the securities with low P / E and negatively - on securities with high P/E.

It is important to look closely at the applicability of some assumptions of the classic financial theory based on the EMH. The first assumption is that all investors are rational. The theory supposes that having all necessary information about stocks or bonds individual investors make the correct choice, thus leading to maximum personal wealth and happiness. They never ignore important information and their behavior is always rational. However, behavioral economics a study of human behavior on the financial market has denied this assumption.

Emotions make people interpret information in a wrong way, thus leading to distortion in estimation of the probability of winning and making wrong decisions. For instance, if offered a choice regarding a roll of coins tails, a person will obtain 200 rubles, and in a roll of an eagle the individual will obtain nothing; or by refusing the offer he will earn $100. Most people prefer the second option because they consider it more reliable. However, if we change the rules of the game and assume that a roll of the coin results in tails, a person loses 200 rubles, and the eagle obtains nothing, or simply refuses to play and pays $100. Research indicates that most players prefer the first option.

These two games are a mirror of each other, so in terms of the classic theory a person in both cases should make the same decision. But the typical decision is explained due to the fact that the defeat is perceived as more painful than winning, so the individual is ready to choose the riskier option in order to have the opportunity not to lose a single dollar. This example shows that the mechanism of choosing in the decision-making process is based on operation of parallel neuronal systems. An automatic involuntary system provides a quick response to changing conditions, but it often fails and leads to an economically suboptimal solution.

This system arose before any other system of decision-making and often poorly adapted to modern economic realities. Perhaps that is why it was the need for forming any system which would adjusted the activities of involuntary mechanisms. To understand mechanisms of human behavior on the one hand, psychic automatism of human irrationality should be considered. On the other hand, the role of rational decision-making mechanisms should not be exaggerated.

The second important assumption within the classic economic theory is that all investors act similarly. According to this idea, all investors have the same goals and the same investment horizons. Having the same information they make the same decisions. But in reality, this assumption does not work properly. Since people are different, their preferences are not the same: one can buy stocks and keep them for 30 years, but another buys and sells every day, speculating on the market.

The third assumption is that the price is constantly changing. The classic financial theory supposes that share prices or exchange rates move continuously from one value to another, they cannot jump on a few items at once. In the reality prices constantly change. Often these changes are not sufficient and occur when brokers rounded prices, skipping the intermediate values. Large jumps are rarer and may occur, for example, when there is a quantitative mismatch of orders to buy and sell shares, so the players begin to rapidly raise or lower the price until equilibrium is established.

The fourth assumption is that the price changes are similar to the Brownian movement. The bulk of price fluctuations on the market take place in a rather small range, and major changes are very rare, and the frequency of their occurrence decreases very rapidly. After studying the behavior of the Dow Jones index for 100 years, Mandelbrot discovered that actual fluctuations in the index are far beyond the Brownian model and on this basis proposed that the standard financial model is wrong. Mandelbrot proposed using the FMH instead of the EMH and was the first person who fixed the fact of market persistence – the ability of a state to exist longer than the process which created it. According to him, financial markets have a long-term memory (Mandelbrot, Benoit, & van Ness, 1968).

Further development of Mandelbrots' concepts was conducted by Greene and Fielitz (1977) by proving presence of a long-term dependence in prices of the stocks in the New York Stock Exchange. Booth, Kaen, and Koveos (1982) also confirmed that some financial data have a long-term memory. Helms et al. (1984) based his analysis on prices on futures and also proved the fact of market persistence. The concepts of the FMH were actively popularized by Peters (1991, 1994). The FMH theory combines fractals and other concepts from chaos theory with traditional quantitative methods to explain and predict the market behavior. FMH considers the daily randomness of the market and anomalies such as market crashes and stampedes.

The FMH is based on the following principles:

1. The market is stable when it consists of investors, who cover a large number of investment horizons. This ensures there is ample liquidity for traders.
2. The information set is more related to market sentiments and technical factors in the short term than in the longer term period. As investment horizons increase, long-term fundamental information dominates.
3. If an event occurs which questions the validity of fundamental information, long-term investors either stop participating in the market or begin trading based on the short term information set. When the overall investment horizon of the market shrinks to a uniform level, the market becomes unstable.
4. Prices reflect a combination of short–term technical trading and long–term fundamental valuation.
5. If a security has no tie to the economic cycle, then there will be no long–term trend. Trading, liquidity, and short-term information will dominate.

The FMH states that information is valued according to the investment horizon of an investor. As soon different investment horizons value information differently, the diffusion of information is also uneven. In a moment of time, prices may not reflect all available information, but only information which is important to a specific investment horizon. The FMH applies an economic and mathematical structure to the fractal market analysis so it is possible to understand the behavior of markets.

Although a sufficient number of studies are devoted to the problem of market persistence and long-term memory, there is no unified methodology. This causes further development of this issue, especially in the context of long-term memory identification and methodology of market persistence estimation.

LONG-TERM MEMORY AND PLASTICITY AS BASIC PROPERTIES IN THE FRACTAL STRUCTURE OF FINANCIAL MARKETS

The precise definition of the fractal is absent in the extant scholarly literature. Usually it is pointed out that “fractal” came from the Latin “fractus” and close to the English word of fraction or fractional. Therefore, from the mathematic point of view, fractal is a plurality with a fractional (fractal) dimension. The fractal dimension characterizes the way how an object or a time series fills space. In addition, it describes the structure of an object when the zoom factor is changing or while zooming the subject. Under zoom factor the scope escalation is meant. For physical (or geometric) fractals, such conversion occurs in space. The fractal dimension of the time series measures how rugged is the time series itself. The direct line should have a fractal dimension equal to its classical geometrical (Euclidean) dimension.

The fractal dimension D is a critical dimension, in which measure changes its value from 0 to ∞. Nevertheless, the topological dimension (the Lebesgue dimension) is always an integer, so for its D can take the following values:

1. D = 0 for a point;
2. D = 1 for a line (e.g., an ellipse, a square);
3. D = 2 for a surface (e.g., a square area);
4. D = 3 for an area (e.g. acube).

The fractal dimension of random time series is 1.5 and represents a zoom function changing over time. The fractal dimension of the time series is extremely important because it recognizes that the process may be somewhere between deterministic (the line with fractal dimension of D = 1) and random (fractal dimension of D = 1,5). The statistics of time series with fractal dimensions different from 1.5, is in great extent deviant from the Gaussian statistics, and not necessarily located within the normal distribution.

Fractal is an attractor (a limit and a goal) for the movement of the chaotic system. Why are these notions identical? In a strange attractor as well as in a fractal while increasing it reveals more details (i.e., it triggers the principle of self-similarity). As much as the size of the attractor is changed it is always in the same proportion. The time series is considered fractal when it exhibits a statistical self-similarity; namely, this property is enjoyed by all ranks of financial assets quotations. The self-similarity could be seen during reading ordinary graphs. For instance, it is impossible to distinguish minute, hourly, and daily charts of any product because they are similar and monotonous. In technical analysis, a typical example of a fractal is “Elliott Waves” which construction is also based on the principle of self-similarity.

An additional idea rooted in fractality regards non-integer dimensions which are usually referred to as a one-dimensional, two-dimensional, or three-dimensional integer world. However, there may be a non-integer dimension such as 2.58 (i.e., located between two-axe and three-axe dimensions). Mandelbrot (1968) called such dimensions fractals. This idea originates from the opinion that the three-dimensional measurement of the real sphere or cube is inadequate, as soon as in the real world it could be hardly found a perfect sphere or a cube, without scratches or any other inaccurateness. In order to describe complex objects, other measurements should exist. Such measurement of incorrect fractal shapes introduces the concept of a fractal dimension.

From the point of view of classical Euclidean geometry, a crumpled sheet of paper will be a three-dimensional sphere. However, in reality it is still only a two-dimensional sheet of paper even if it is crumpled. Hence, it can be assumed that the new object will have a dimension greater than two but less than three. It hardly fits the Euclidean geometry, but can be well described by fractal geometry which argues that the new object will be located in the fractal dimension equal approximately to 2.5 (i.e., will have a fractal dimension of about 2.5). The physical meaning of this dimension is very simple in that in the classical three-dimensional space, some parts remain empty because of gaps and holes naturally presented in a crumpled sheet of paper.

When applying this theory to the financial markets, we can assume that markets are characterized by various degrees of plasticity defined as the capacity to take and retain form. This definition means that markets can be molded to various degrees in terms of their shapes and functions, and that they are able, to various degrees to retain such changes in their properties even after the molding effort ceases. Thus, plasticity is a dual construct since it requires both fluidity defined as the capacity to take form, and stability defined as the capacity to retain form. All markets are plastic even though their degree of plasticity can change. Therefore, the interplay between fluidity and stability helps us understand market dynamics in more detail.

The term "market plasticity" encapsulates the dynamic and socially constructed nature of markets better than other available terms. Expressions such as ''dynamics", "development", and "evolution" lean more toward the process of market change than the characteristics of markets that allows dynamics. Other constructs such as "change" and "fluidity" neglect what is arguably a critical facet of market dynamics, namely its dual character of both fluidity and stability.

There are two important consequences of the plastic character of markets as defined above. First, the ability to retain form allows markets to give form to other entities by, for example, affecting the shape of a particular exchange object, the mode of a specific economic exchange, or the characteristics of an exchange agent. Markets are thus performative in the broad sense of the term (Law & Urry, 2004). Second, the ability to take form allows markets to host multiple forms simultaneously. As actors enact ''their'' market, markets tend to multiply into overlapping versions (Kjellberg & Helgesson, 2006).

In the natural sciences, plasticity is a construct used to describe suppleness and deformation in various contexts. For example, in physics plasticity is defined as a deformation of a material undergoing nonreversible changes in shape in response to forces applied (Bigoni, 2012; Lubliner, 2008). In biology, the term "plasticity" is most often used to discuss "phenotypic plasticity"; that is, the ability of organisms to alter their phenotypes (observable characteristics) in response to changes in the environment (West-Eberhard, 1989). "Neuroplasticity" is the capability of the cerebral cortex to alter its physical structure and functional organization (Pascual-Leone et al., 2005).

Systems theory differentiates between structural and organizational plasticity. The former refers to a social system's ability to drift toward greater congruence through recurring perturbations, while the latter refers to the system's ability to neutralize external structural changes by making internal structural changes (Forrester, 1961; Maturana, 1978; Sterman, 2000). In philosophy, Malabou (2008, 2010) discusses the concept of plasticity with reference to a three-fold definition: (a) the capacity to receive form; (b) the capacity to give form; and (c) the powerful rupture or annihilation of all forms (possibly inspired by the notion of plastic explosives). In the social sciences, the plasticity construct is used less often and as a more peripheral concept than in the natural sciences. For example, in sociology, the term "plasticity" is loosely referred to as variability (Turner et al., 1995); hence, the difficulty of describing, defining, or demarcating the boundaries of something (Donaldson, 1987).

Two explicit uses of the term plasticity can be detected in economics. First, Alchian and Woodward (1988) use asset plasticity "to indicate that there is a wide range of discretionary, legitimate decisions within which the user may choose" (p.69). This characteristics is said to explain which resources are vulnerable to morally hazardous exploitation; hence, giving agents opportunities to bias their actions toward their own interests. Second, Strambach (2010) discusses the notion of institutional plasticity, emphasizing that institutions are both enabling and restraining. Their plasticity character is linked to interpretative flexibility, which in turn depends on the sanctions (e.g., social and legal) associated with a particular institution.

Because actors take action in situations where firm, industry, regional, national, and international institutions overlap, there are opportunities for new combinations of earlier institutional components. Finally, complementarity between institutions is identified as having an ambiguous role, with contributing to both stability (via lock in) and fluidity (through accumulation of incremental changes). In marketing, Alderson (1957, p. 277) used the term plasticity to signify the potentiality for remolding and subsequently responding differently. However, the plasticity concept does not belong to the core lexicon used by organization theorists or strategy researchers.

During the literature review, five main facets of plasticity were identified: the abilities to take form, retain form, give form, annihilate form, and change function. These facets are to compare our proposed definition of plasticity (market plasticity) with definitions of other identified meanings and use of the term; most of existing plasticity conceptions emphasizes the duality of taking and retaining form. Malabou's (2008, 2010) definition of plasticity is the most extensive, because it also acknowledges performative and destructive forces of plasticity. Additionally, plasticity definitions, being rooted in the natural sciences, differentiate between the plasticity of form and the plasticity of function. However, differentiating structural and functional plasticity becomes increasingly challenging when investigating social phenomena.

THE HURST INDEX AS A MEASURE FOR THE FRACTAL STRUCTURE AND LONG-TERM MEMORY OF FINANCIAL MARKETS

The main method of the fractal time series study is R/S-analysis or the method of rescaled range. It was suggested by the hydrologist Harold Edwin Hurst (1951) who in the mid-20th century worked at the Nile dam project (p. 205). The task was to calculate the required volume of the dam reservoir, filling of which occurred due to various natural sources: rainfalls, floods, etc. Usually, in such cases, hydrologists start with the assumption that the water level in the river is a random series where the value of the water level in the following years do not depend on the previous ones. But having read about floods in the last 800 years, Hurst discovered the following regularity: the year the high water level is usually followed by another year with a high level, and the year with a low level of water by another year with low levels. It appeared like a cycle with an unpredictable period. A standard statistical analysis revealed no significant correlations between observations, so Hurst had to develop his own methodology.

There are at least two variations of fractal dimension – D and A. The fractal dimension D (where D is the dimension of time track – an assessment of the degree of affectation series) is defined due to Equation 1:

$$D = 2 - H \tag{1}$$

Mandelbrot and van Ness (1968) has demonstrated that the fractal dimension is the reciprocal value of the Hurst exponent (H). For instance, if H = 0.5, the fractal dimension is equal to 2 (1/0.5), and if H = 0.8, the fractal dimension is equal to 1.25 (1/0.8). Therefore, the fractal dimension of Mandelbrot A (where A is the dimension of the probability space – estimationof the thickness of tails in the probability density function) is calculated due to Equation 2:

$$A = 1/H \tag{2}$$

The Hurst exponent can be defined on the interval $[0,1]$, and is calculated within the following limits:

$0 \le H < 0,5$ – Data is fractal, the FMH is confirmed, «heavy tails» of distribution, antipersistent series, negative correlation in instruments of value changes, pink noise with frequent changes in direction of price movement, trading in the market is more risky for an individual participant;

$H = 0,5$ – Data is random, the EMH is confirmed, movement of asset prices is an example of the random Brownian motion (Wiener process), time series are normally distributed, lack of correlation in changes in value of assets (memory of series), white noise of independent random process, traders cannot «beat» the market with any trading strategy;

$0,5 < H \le 1$ – Data is fractal, the FMH is confirmed, «heavy tails» of distribution, persistent series, positive correlation within changes in the value of assets, black noise, the trend is present in the market.

Hurst took the Equation from Einstein's work on Brownian motion of particles as a reference point per Equation 3:

$$R = \sqrt{T} \text{, где} \tag{3}$$

where R – the distance covered by a Brownian particle in time T; T – time index.

According to this Equation, a Brownian particle moved by a distance equal to the square root of time spent on this movement. If $H = 0,5$, a system runs in the time T the same distance as a Brownian particle. With large values of H a system goes a considerable distance in the same time T in comparison with a Brownian particle. The Hurst exponent calculation can be carried out according to the following Equation (4, 5):

$$R \setminus S = (aN)^H \text{, consequently} \tag{4}$$

Table 1. The values of the variations of the fractal dimension

Hurst Index (H)	$H \approx 0$	$H = 0,5$	$H = 1$
Fractal Dimension D	$D \approx 2$	$D = 1,5$	$D = 1$
Fractal Dimension A	$A \to \infty$	$A = 2$	$A = 1$
	Straight line	Random Series	Infinite Linear Trend

$$H = \frac{\log(R \setminus S)}{\log(aN)} \text{, where} \tag{5}$$

H – The Hurst index;
S – The mean-squar deviation of an observations series x;
R – The amplitude of the accumulated deviations Zu;
N – The number of observation periods;
a – The given constant, a positive number. Hurst has empirically calculated this constant for relatively short-term time series of natural phenomena. The constant is $0,5$.

Even using $0,5$ as the constant, with a small number of observations N the Hurst index tends to evaluate random series as persistent (having a trend), overstating H. Therefore, for further research it is more reliable to use the constant as $a = \pi / 2$ (6).

$$S = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Xi - X\right)^{2}} \text{, где} \tag{6}$$

X – the arithmetic mean of a set of observations x for N periods (7):

$$X = \frac{1}{N}\sum_{i=1}^{N} Xi \tag{7}$$

The amplitude of the accumulated deviation is the most important element in the Equation for calculating the Hurst index. It is calculated as follows Equation (8):

$$R = \max(Zu) - \min(Zu), \tag{8}$$

where Zu - accumulated deviation of series x from the average value X (9):

$$Zu = \sum_{i=1}^{u}(Xi - X) \tag{9}$$

Eric Naiman has improved the Hurst Equation for those cases, when sampling of random variables is represented by a small number of observations (Naiman, 2011) (10):

$$H_T = \frac{\log\left(\frac{R}{S_T}\right)}{\log\left(\pi * \frac{N}{2}\right)}(-0,0011 * ln(N) + 1,0136) \tag{10}$$

It is visible from the Equation of the Hurst index that there some influential factors, namely: an increase of the oscillation amplitude R, reduction of the arithmetic mean deviation S, reduction of the number of observations N.

As it is observed, the dynamics of market prices corresponds to the Hurst index (H) much higher than $0,5$. In other words, the dynamics of market prices and macroeconomic indicators is not accidental, and there are at least two good reasons for this situation. First, information about the market is not immediately considered in the prices. This occurs, inter alia, because of unbalanced access of different market players to the same information. Second, over time, the influence of information is reduced. Therefore, a well-known psychological phenomenon as memory of market is demonstrated. The memory of market can be characterized in four words – the market is inertial. This thesis could be justified via the FMH. The Hurst index is seen helpful to calculate fractal dimension, so it should be interpreted as the necessary element of the FMH.

The Hurst index could be also used as a measure of volatility of the data series. Peters (1994) highlights in his *Fractal Market Analysis: Applying Chaos Theory to Investment and Economics* that in the analysis of stock risks it is preferable to use the fractal dimension instead of the standard deviation. The standard deviation is good while it characterizes variability of random series. If to deal with market as a stochastic process, in this case the use of standard deviation as the main characteristics of risk values is justifiable enough. If to admit that market is not stochastic, but chaotic, fractal dimension as a measure of non-linearity of price movements is much better suited.

Why does an effect of the price inertia in relation to the previous motion appear in the financial markets? This fact can be explained based on the psychology of human memory. The Hurst index of over $0,5$ also confirms the presence of non-volatile memory market – the present depends on the past and the future depends on the present.

As some of the contemporary research of human memory has demonstrated, people daily "lose" up to 25 percent of the information already received. Under the information we refer not only to knowledge acquisition, but also to psychological experiences associated with the process of obtaining such knowledge. For example, if on Monday the market had a strong increase in prices, a trader in that day, of course, remembers the full scope of information related to price increases and is under the impression of such growth. On Tuesday, the trader will retain in memory about 75% of the psychological emotions of the previous day, and of a specific content, which caused a rise in prices. On Wednesday, the percentage of memories will fall to 50%, on Thursday up to 25%, and on Friday will leave only a slight trace of memories.

The percentage of forgetting may vary depending on events in subsequent days. If on Tuesday the rise in prices continues, it will intensify the impression of Monday, and on Wednesday the increase on Monday and Tuesday will be a spectacular event in memory of a trader. The percentage of memory will be more than 75%. If on Tuesday price will decline, on the contrary, the events of Monday will lose their weight more than 50% by Wednesday. That is why the memory of trader must be considered in one continuous chain of events where the latest events will be given greater weight. It reminds us of the calculation of the exponential moving average. Since in the second and third day (Tuesday and Wednesday in our example) the trader remembers most of events of the first day, then this memory will impose a significant imprint on his actions during these days.

Few dare to sell in a strong bull market without sufficient reason. However, after a strong movement a fear of sales will be affected for several days, gradually weakening its impact on a trader. In reality, it often happens that a strong move on Friday is continued on Monday, sometimes grabbing the first half of Tuesday. Strong price changes on Tuesday/Wednesday and weaken by Thursday/Friday. Knowing this and understanding the reasons for such a behavior of the market, one can avoid hasty actions and stop working with the trend. Understanding of market inertia allows us to make an important remark: an investor will better understand the market if he learns to consider it through the eyes of an average trader who largely bases actions on previous market developments. This does not mean the descend level of knowledge of an average trader.

STUDY OF THE AVAILABILITY OF THE FRACTUAL STRUCTURE AND LONG-TERM MEMORY OF THE CURRENCY MARKET WITH THE HURST INDEX

Another example of the long-term memory influence is the currency market activities. Let us calculate the Hurst index for the currency pair EUR / USD with closing prices, the range - 1 day, the number of observations – 20 1. Those who calculate the Hurst index, based on market prices, often stand the arising question of what ranks to explore – data series or data changes. For instance, it could be the logarithm of the current value to the previous one which is usually used in the analysis of market quotations. Analysis has shown that the normalized logarithmic scale of random series of changes is much smaller than the scale of the normalized logarithmic linear (rising or falling) series changes.

As the result, the Hurst index calculated on the logarithms of linear series changes reach huge quantities. Therefore, if we take a series of data that evince some signs of trending, calculate logarithms changes on it, the Hurst exponent of such series will be well above 1. That is why it will be used the classic model of the Hurst index calculation according to the initial data series. The results of our calculations are shown in Table 2.

The results of calculation demonstrate that the market has short-term memory within the short time interval, as H = 0.5964. Further, we have chosen more longitude interval of one year and made the same calculation for the currency pair EUR/USD. The interval is equal to 1 week, the number of observations – 53. The results of calculations are presented in Table 3.

The results demonstrate that the market has memory in the long-term interval, which is equal to 1, the Hurst index is higher and constitutes 0.6999. Thus, our calculations show that market events and economic indicators are not random. This conclusion was reached for all the calculated data series at different time intervals. The market is inert and has a memory. Moreover, the longer the interval, the more pronounced the market memory. This confirms the validity of the FMH which is seen as an alternative to the EMH. Since the Hurst index can be helpful for calculating fractal dimension, it is considered a necessary element of the FMH.

CONCLUSION AND RECOMMENDATIONS

Key concepts of the classical financial theory (e.g., pricing model CAPM, portfolio theory of Markowitz, Black-Scholes Equation), on which are built the vast majority of methods used in the practice of commercial and investment banks, investment funds, insurance companies and other financial institutions around the world, are based on the assumption that the feasibility of the efficient market hypothesis. If earlier anomalies and sharp stock market crashes have caused debates of supporters and opponents of

Table 2. Hurst exponent calculation results on the closing prices of the currency pair EUR / USD (N=20)

Date	Close Price	$(x_i - X)$	$\Sigma(x_i - X)$
May, 4 2014	1,38719	0,0037	0,0037
May, 2 2014	1,38714	0,0037	0,0074
May, 1 2014	1,38699	0,0035	0,0109
April, 30 2014	1,38682	0,0034	0,0143
April, 29 2014	1,38130	-0,0022	0,0121
April, 28 2014	1,38520	0,0017	0,0139
April, 27 2014	1,38392	0,0005	0,0143
April, 25 2014	1,38366	0,0002	0,0145
April, 24 2014	1,38270	-0,0008	0,0138
April, 23 2014	1,38172	-0,0017	0,0120
April, 22 2014	1,38071	-0,0027	0,0093
April, 21 2014	1,37917	-0,0043	0,0050
April, 20 2014	1,38143	-0,0020	0,0030
April, 18 2014	1,38158	-0,0019	0,0011
April, 17 2014	1,38109	-0,0024	-0,0013
April, 16 2014	1,38240	-0,0011	-0,0023
April, 15 2014	1,38111	-0,0023	-0,0047
April, 14 2014	1,38156	-0,0019	-0,0066
April, 13 2014	1,38473	0,0013	-0,0053
April, 11 2014	1,38869	0,0052	0,0000
Arithmetic mean X	**1,383456**	**Maximum**	**0,0145**
Standard deviation S	**0,0027**	**Minimum**	**-0,0066**
Scope R	**0,0145-(-0,0066)=**		**0,0211**
Normalized scope R/S	**0,0211/0,0027=**		**7,8148**
Log(R/S)	**Log(7,8148)=**		**0,8929**
Log(N*π/2)	**log(20*3,1416/2)=**		**1,4971**
Hurst index H	**0,8929/1,4971=**		**0,5964**
Calculation R/ST	**7,8148*0,998752+1,051037 =**		**8,8561**
Log(R/ST)	**Log(8,8561)=**		**0,9472**
Hurst index HT	**0,9472/1,4971*(-0,0011*Ln(20)+1,0136) =**		**0,6392**

Table 3. Hurst exponent calculation results on the closing prices of the currency pair EUR / USD (N=53)

Date	Close Price	$(x_i - X)$	$\Sigma(x_i - X)$
February, 1 2015	1,1316	-0,1740	-0,1740
January, 25 2015	1,1288	-0,1768	-0,3508
January, 18 2015	1,1208	-0,1848	-0,5357
January, 11 2015	1,1569	-0,1487	-0,6844
January, 4 2015	1,1842	-0,1214	-0,8058
December, 28 2014	1,2003	-0,1053	-0,9111
December, 21 2014	1,2176	-0,0880	-0,9991
December, 14 2014	1,2228	-0,0828	-1,0820
December, 7 2014	1,2462	-0,0594	-1,1414
November, 30 2014	1,2286	-0,0770	-1,2184
November, 23 2014	1,2452	-0,0604	-1,2788
November, 16 2014	1,2390	-0,0666	-1,3454
November, 9 2014	1,2524	-0,0532	-1,3987
November, 2 2014	1,2454	-0,0602	-1,4589
October, 26 2014	1,2525	-0,0531	-1,5120
October, 19 2014	1,2671	-0,0385	-1,5505
October, 12 2014	1,2763	-0,0293	-1,5798
October, 5 2014	1,2628	-0,0428	-1,6227
September, 28 2014	1,2517	-0,0539	-1,6766
September, 21 2014	1,2685	-0,0371	-1,7137
September, 14 2014	1,2829	-0,0227	-1,7364
September, 7 2014	1,2965	-0,0091	-1,7455
August, 31 2014	1,2951	-0,0105	-1,7561
August, 24 2014	1,3133	0,0077	-1,7484
August, 17 2014	1,3243	0,0187	-1,7297
August, 10 2014	1,3399	0,0343	-1,6954
August, 3 2014	1,3411	0,0355	-1,6599
July, 27 2014	1,3431	0,0375	-1,6225
July, 20 2014	1,3432	0,0376	-1,5849
July, 13 2014	1,3524	0,0468	-1,5381

continued on following page

Table 3. Continued

Date	Close Price	$(x_i - X)$	$\Sigma(x_i - X)$
July, 6 2014	1,3609	0,0553	-1,4828
June, 29 2014	1,3596	0,0540	-1,4288
June, 22 2014	1,3649	0,0593	-1,3696
June, 15 2014	1,3599	0,0543	-1,3153
June, 8 2014	1,3542	0,0486	-1,2667
June, 1 2014	1,3642	0,0586	-1,2081
May, 25 2014	1,3631	0,0575	-1,1506
May, 18 2014	1,3634	0,0578	-1,5381
May, 11 2014	1,3695	0,0639	-1,4828
May, 4 2014	1,3760	0,0704	-1,4288
April, 27 2014	1,3870	0,0814	-1,3696
April, 20 2014	1,3833	0,0777	-1,3153
April, 13 2014	1,3815	0,0759	-1,2667
April, 6 2014	1,3885	0,0829	-1,2081
March, 30 2014	1,3703	0,0647	-1,1506
March, 23 2014	1,3753	0,0697	-0,5064
March, 16 2014	1,3794	0,0738	-0,4326
March, 9 2014	1,3915	0,0859	-0,3468
March, 2 2014	1,3878	0,0822	-0,2646
February, 23 2014	1,3802	0,0746	-0,1900
February, 16 2014	1,3740	0,0684	-0,1216
February, 9 2014	1,3693	0,0637	-0,0579
February, 2 2014	1,3635	0,0579	0,0000
Arithmetic mean X	**1,30562**	**Maximum**	**-0,0579**
Standard deviation S	**0,0769**	**Minimum**	**-1,7561**
Scope R	**-0,0579-(-1,7561)=**		**1,6982**
Normalized scope R/S	**1,6982/0,0769=**		**22,0816**
Log(R/S)	**Log(22,0816)=**		**1,344**
Log(N*π/2)	**Log(53*3,1416/2)=**		**1,9204**
Hurst index H	**1,344/1,9204=**		**0,6999**
Calculation R/ST	**22,0816*0,998752+1,051037=**		**23,1051**
Log(R/ST)	**Log(23,1051) =**		**1,3637**
Hurst index HT	**1,3637/1,9204*(-0,0011*Ln(20)+1,0136)=**		**0,7166**

the EMH about the applicability of such an assumption, after the global crisis in 2008, it became clear that the EMH does not fully apply in practice. If considering financial markets as an analogue of the brain neural networks and fractals (e.g., investors with different investment horizons) as an analogue of neurons, the most interesting impact could be demonstrated by application of the FMH. The FMH is one the alternatives to the EMH. Our analysis verifies the fact of fractality in the most of contemporary markets. The classical methods of risk estimation do not take into account the fractal structure of the market, while this is the main advantage of the fractal approach.

The results of our calculations demonstrate that market events and economic indicators are not random phenomena. The market has a fractal structure and a long-term memory and plasticity. This conclusion has been reached for all data series in different time intervals. Therefore, the FMH can be applied successfully to economic phenomena. The assumption that investment decisions can be predicted based on the analysis of neural mechanisms of the information influence on fractals will allow to open new horizons in understanding of the investor behavior in financial markets. In order to understand the process of investment decision-making, the following scheme could be recommended:

1. On the first step, the Equationtion of a problem creates a view about the purpose and context of the decision. It integrates information about the internal conditions of the organism and environmental factors, such as famine or level of threat in the context of future action.
2. The next step is determined by the value or valuation of the choosing procedure with particular behavioral alternatives.
3. On the third step, alternative solutions are compared and the best solution is selected. This step is called action selection.
4. After implementation of a selected action the results are calculated and efficiency is evaluated.
5. The last step is training. Training means updating information stored in the memory, so that all subsequent steps would be implemented with greater efficiency.

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ENDNOTE

1 The data used for this calculation was retrieved at the FOREX - FXTMPIRE // http://ru.fxempire.com/currencies/eur-usd/tools/historical-data/