ЕМИРИЧНО ИЗСЛЕДВАНЕ ВЪРХУ ИЗВЕСТИЦИОННАТА ТЕОРИЯ „КУЛИ ВЪВ ВЪЗДУХА“

доц. д-р Боряна Богданова
СУ „Св. Климент Охридски“, Стопански факултет

„THE-CASTLES-IN-THE AIR" INVESTMENT THEORY: AN EMPIRICAL STUDY

Assoc. Prof. Boryana Bogdanova, PhD
Sofia University „St. Kliment Ohridski",
Faculty of Economics and Business Administration

Abstract: *The goal of this paper is to study empirically the Malkiel's „castles in the air theory". The research framework builds up on two hypotheses. The first one considers the Greenspan's „irrational exuberance" as being the core driver behind boosted stock prices, which eventually results into a blown-off bubble. The other one views the bubble occurrence as a superimposition of several cyclical waves reaching their peaks (or possibly bottoms) simultaneously.*

Key words: *stock market bubble, investment theory, wavelet analysis, EMA trading rule*

Introduction.

As summarized by Burton Malkiel (1) two investments theories are broadly adopted by professionals – these are the firm foundation theory and the „castles-in-the air" theory. While the first one relies heavily in trading assets with identified discrepancies in asset's price and its intrinsic value, the second theory is engaged with predicting the crowd mainly on the grounds of psychology or as recently argued on patterns recognition. The goal of this paper is to study empirically the „castles in the air theory", in particular two hypotheses are tested. On one hand, the Greenspan's „irrational exuberance" is considered as being the core driver behind boosted stock prices, which eventually results into the „self-fulfilled prophecy" of a blown-off bubble. On the other hand, if viewed through the lens of modern Econometrics or even further, through the lens of Econophysics, a bubble occurrence might come naturally in the form of a superimposition of several cyclical waves reaching their peaks (or possibly bottoms) simultaneously.

It should be noted, however, that these two hypothesis are not necessarily mutually exclusive, furthermore under certain circumstances they might be viewed as complements. Nevertheless, confirmation or rejection of each of them has its own important implications. While confirmation of the first hypothesis would be supportive to behaviorists as opposed to proponents of Efficient-market hypothesis (2) and vice versa, it is in fact of little use for predictive purposes. On the other hand, verification of the second hypothesis would foster better understanding of different bubble structures, which in turn might provide hints for upcoming snowball processes. Furthermore, a recent research (3) suggests that the financial cycle should be at the core of one's understanding of the macroeconoy. In particular, dealing with the financial cycle requires policies that take into account boom and bust phases. The latter fact combined with the finding that the financial cycle is longer than the business cycle, highlights the importance of studying cyclical structures in stock market data.

The research is carried out over a long period of time so as to include the Black Monday crisis, the Dot-com bubble as well as the 2008 financial crisis. The research methodology makes use of simple but widely applied tools from technical analysis; at the same time, it employs cutting-edge research tools from the field of Econophysics (4). The latter approach allows the analyst to view not just the top of the iceberg but also to be aware of what is hidden underwater.

Methodology

A recent book devoted to the Bulgarian stock exchange (5), p. 131, suggests that the bubble requires two inputs, the first one is cheap money, while the second one is something fashionable. However, even when investors realize that both of the bubble ingredients are present and hence the market peak is pretty near, they keep on investing driven by the greedy expectations that some additional quick profit might be still generated. In this framework, going out of the market in time is of crucial importance, consequently, investors watch closely fundamental indicators. Yet, under presence of informational asymmetries, technical analysis is often engaged in order to infer on the crowd's behavior and decide on whether to stay on or leave the market.

From this perspective, this paper applies technical analysis so as to test the "self-fulfilling prophecy" hypothesis that supports behaviorists. For this purpose, we engage one of the most commonly applied trading strategies based on dual moving average crossover rule. As explained in (6) this rule compares the values of two moving averages (MA) of different lag lengths. When the short-term MA falls bellow the long-term MA, than this is a sell signal. Alternatively, investors receive a buy signal when the short-term moving average closes above the long-term MA. In addition, a 1 percent band filter is used to allow for false signals. As argued in (7), exponential moving average (EMA) is considered as more adaptive since it weights heavily recent prices and puts less weight to observations distant in time. For the calculation of EMA of lag N, the following formula is used:

$$EMA_N(t) = EMA_N(t-1) + \frac{2}{N+1}\left(P(t) - EMA_N(t-1)\right) \qquad (1)$$

Among the most commonly used couples of short- and long-term exponentially weighted MA is EMA_{16} and EMA_{60}. They are used in this paper as well.

While application of EMA crossover rule is quite straightforward, identification of cyclical patterns is a way more challenging task. Typically, Fourier spectrum is used so as to infer on presence of cycles. However, its major drawback is the lack of time resolution, i.e. changes and breaks in patterns could not be captured. As advised in (8) this issue is resolved when instead of analyzing the Fourier spectrum, one uses the wavelet spectrum. The latter provides resolution both in frequency and time. The idea behind wavelet spectrum analysis is briefly described with the following text, which is based on the discussion in (9).

A function $\psi(t) \in L^2(\mathbb{R})$ is said to be a mother wavelet if it satisfies the so called "admissibility condition", which is a decay condition and ensures that the function is well localized both in time and frequency. For functions with sufficient decay the admissibility condition is equivalent to requiring that

$$\Psi(0) = \int_{-\infty}^{\infty} \psi(t)dt = 0, \tag{2}$$

where $L^2(\mathbb{R})$ denotes the set of square integrable functions and $\Psi(\omega)$ denotes the Fourier transform of $\psi(t)$. A family of wavelet daughters $\{\psi_{\tau,s};\ s,\tau \in \mathbb{R}, s \neq 0\}$ can be obtained by scaling and translating the mother wavelet ψ :

$$\psi_{\tau,s} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right), \tag{3}$$

where s is a scaling factor controlling for the width of the wavelet and τ is a translation parameter controlling its location. Given a time series $x(t) \epsilon L^2(\mathbb{R})$ its continuous wavelet transform with respect to the wavelt ψ is defined as follows:

$$W_{x;\psi}(\tau,s) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)dt, \tag{4}$$

where the asterisk denotes complex conjugate. For simplicity of notation the wavelet transform $W_{x;\psi}(\tau,s)$ will be denoted by W_x in the text that follows.

Similarly to the case of Fourier analysis, a wavelet power spectrum is defined as follows:

$$WPS_x = |W_x|^2. \tag{5}$$

For empirical purposes Eq.(5) would be calculated and its local maxima would be analyzed in order to infer on presence of cyclical patterns.

Empirical analysis

Data

For the purpose of identifying cyclical patterns through continuous wavelet transforms, it is reasonable to consider a longer period of observations so as to capture not only high frequency patterns but also to identify long term tendencies. Therefore, we apply wavelet spectrum analysis to time series spanning over a period of 45 years, i.e. from the beginning of 1971 to end 2015. Monthly sampling rate is adopted as we are interested in the presence of cycles, hence, using weekly or daily data would not contribute any additional value to our analysis, rather it would deteriorate the computational efficiency. The augmented Dickey-Fuller (ADF) test reported in *Table 1* does not reject the unit-root hypothesis, which means that the closing price series are nonstationary therefore as advised in (10) we transform them into logarithmic returns.

Table 1: Descriptive statistics of NASDAQ Composite monthly closing prices and log-returns series. The p-values associated with the Augmented Dickey-Fuller test as well as the Jarque-Bera test are reported in brackets under the respective test statistics values.

	Closing prices	*Log-returns*
Mean	1281.62	0.0073
Median	704.33	0.0141
STD	1281.57	0.0619
Skewness	1.06	-0.86
Kurtosis	3.34	5.90
ADF statistics	1.78	-20.12
	(98.19%)	(0.10%)
JB statistics	103.74	254.31
	(0.10%)	(0.10%)

The last column of *Table 1* provide descriptive statistics for the transformed data sequence. According to the ADF test, the log-return series are stationary. Yet, the rest of the reported statics suggests that log-returns do not follow normal distribution, in particular leptokurtic behavior is observed.

The reader might find visual representation of the closing prices as well as of the log-returns series at *Figure 1*. Inspecting panel (a) of this figure, one might easily note the Dot-com bubble as well as the financial crisis of 2008. Yet, analyzing panel (b), we might also note significant increase in volatility during the stock market crash of 1987 (Black Monday). Nevertheless, due to the fact that NASDAQ Composite is heavily high-tech loaded, the Dot-com bubble is most clearly pronounced.

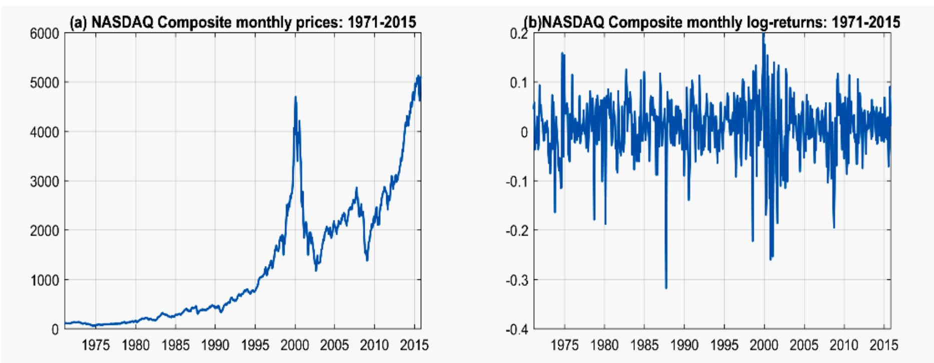

Figure 1: (a) NASDAQ Composite monthly closing prices for the period 1971-2015.
(b) NASDAQ Composite monthly log-return series for the period 1971-2015.

The second part of our analysis involves application of technical analysis. The goal is to predict the crowd behavior in times of turmoil. To be specific, we are interested if there are sell signals just before the bubble pops. Therefore, we analyze NASDAQ Composite daily closing prices over two four-year periods covering the last two significant bubbles. The first period spans from Jan-1999 to Dec-2002, while the second is from Jan-2005 to Dec-2008.

Figure 2: (a) NASDAQ Composite daily closing prices for the period Jan-1999 – Dec-2002. (b) NASDAQ Composite daily closing prices for the period Jan-2005 – Dec-2008

Figure 2 (a) illustrates daily closing prices of NASDAQ Composite for the period of the Dot-com bubble, while *Figure 2* (b) describe price movements during the subprime mortgage bubble. The periods of significant price decrease are of specific interest. Through application of exponentially weighted moving average crossover trading strategy, we would inspect if sell signals occur prior to significant price drops and if so, how long it takes for the panic to spread over the market. It should be noted that application of simple smoothing techniques does not rely on any assumptions such as stationarity or normality therefore no further data tests are performed.

Results and discussion

We first study presence of cyclical patterns through analysis of the wavelet spectrum. In particular, we apply Eq.(5) to the monthly log-returns of NASDAQ Composite for the period 1971-2015. Figure 3 presents the estimation output.

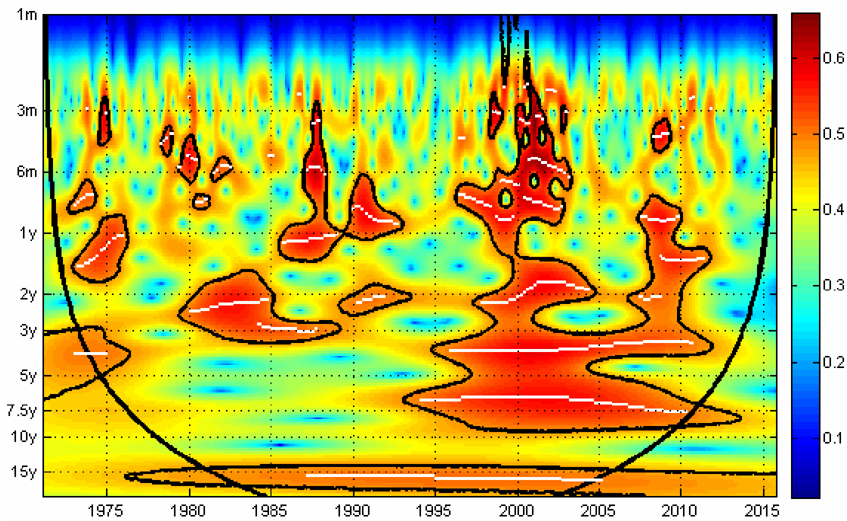

Figure 3: Wavelet power spectrum of NASDAQ Composite log-return series for the period 1971-2015

As might be seen from the figure, the results are presented in the form of a color map, due to the fact that wavelet power spectrum provides three-dimensional description: each pixel of the map corresponds to a particular value of WPS_x at a specific point in the time-frequency plane. The x-axis corresponds to the time scale and the y-axis – to the frequency scale. Similarly to a geography map, each value of WPS_x is denoted by color. The utilized color code is presented next to the map. In order to ease interpretation of results, the utilized frequencies are converted into time units, where the finest scale corresponds to one week, and the coarser scale – to five years. Additionally, the statistically significant coherencies are determined on the basis of Monte Carlo experiments[14] and then they are contoured on the map. The cone of influence is plotted with tick black line and it represents the region in which the transform suffers from edge effects. To further ease interpretation of results the local maxima of WPS_x is denoted by white contour.

Considering *Figure 3* several findings might be outlined. First of all, a financial cycle of 15-17 years length might be identified throughout the period under study (since late 1970s till end of 2015). This finding is in compliance with the paper of Bario (3), where the author states that the financial cycle is of longer duration (approximately 16-20 years) than the traditional business cycle. Nevertheless, other significant cycles might be also distinguished. Analyzing earlier periods, we might note that apart from the 15-17 years financial cycle, a cyclical pattern of 2-3 years is observed since early 1980s. Furthermore, during the time of 1987 stock crash, we might note clearly pronounced periodicities at about 1-year frequency band. The latter results are supportive to the hypothesis that a popping bubble might be a natural consequence of the superimposition of several cyclical waves. It is interesting to note that we have identified both the typical financial cycle (at 15-17 years frequency band) and the typical business cycle (at 2-3 years frequency band) as well as some short-term fluctuations contributing to the cyclical patterns. Moving forward in time, we might note increased complexity in the observed patterns. To be specific, a new cycle of 7-7.5 years emerges in the mid 1990s and lasts till 2011. Again significant short-term cycles are present during the Dot.com bubble and the financial crisis of 2008. While the latter are hardly predictable and might come as a result of irrational behavior of investors, including panic, the well-established cycles of 15-17 years, 7-7.5 years and 2-3 years are subject to modelling and their peaks and bottoms might be predicted. These findings have important implications for policy-makers, in particular when carry out policies that take into account boom and bust phases.

14 For additional details the reader is referred to (9).

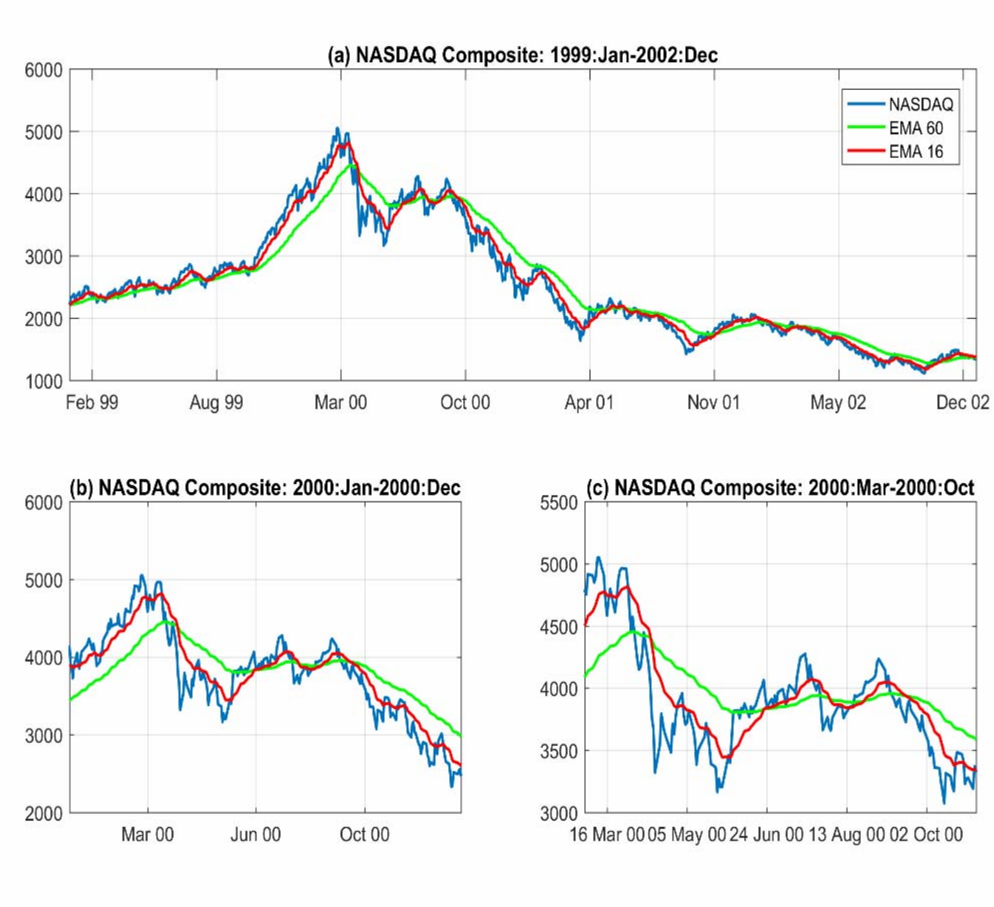

Figure 4: Sell signals during the Dot-com bubble

While Figure 3 suggests that in times of turmoil superimposition of several cyclical waves of long- and mid-term length is present, it also confirms that each significant stock market crash is associated with higher frequency patterns. Therefore, as a next step in our analysis, we study daily stock price fluctuations through the lens of technical analysis. In particular, Eq.(1) is applied to the daily closing prices of NASDAQ Composite for the period Jan-1999 – Dec-2002 as well as Jan-2005 – Dec-2008, where $N = 16$ and $N = 60$. The resulting EMA_{16} and EMA_{60} smoothed series are presented at *Figure 4* and *Figure 5*, respectively.

Looking at *Figure 4* (a) one might easily note that the first sell signal appears in Apr-2000 and a second one in Sep-2000. Panels (b) and (c) of the same figure zoom in the crossover points, while *Table 2* and *Table 3* present the percentage relative EMA difference. Following the 1% threshold rule, we find that sell signals came on 13-Apr-2000 and 25-Sep-2000. Yet, more interesting is the finding that on 14-Apr-2000 the market closed at 9.67% decrease in price, which is supportive to our first hypothesis.

Table 2: Relative difference in Apr-2000.

Date	$\frac{EMA_{16}(t)-EMA_{60}(t)}{P(t)}$
4/10/2000	1.49%
4/11/2000	0.61%
4/12/2000	-0.85%
4/13/2000	-2.40%
4/14/2000	-4.99%

Table 3: Relative difference in Sep-2000.

Date	$\frac{EMA_{16}(t)-EMA_{60}(t)}{P(t)}$
9/14/2000	0.86%
9/15/2000	0.52%
9/18/2000	-0.02%
9/19/2000	-0.17%
9/20/2000	-0.23%
9/21/2000	-0.44%
9/22/2000	-0.68%
9/25/2000	-1.03%
9/26/2000	-1.45%
9/27/2000	-1.88%

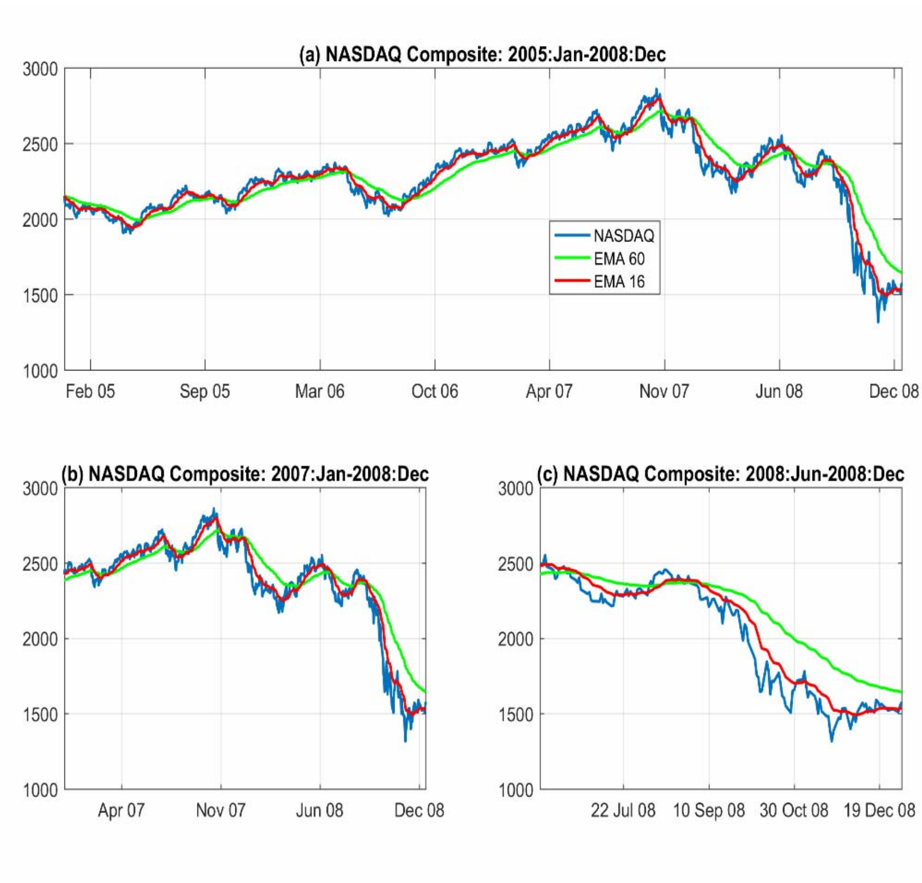

Figure 5: Sell signals during the 2008 financial crisis.

Further evidence might be gained in terms of the 2008 financial crisis. Panel (c) of *Figure 5* indicates that a sell signal appears in Sep-2008. More precisely, looking at *Table 4*, we could note that the signal came on 9-Sep-2008, just two days after Fannie Mae and Freddie Mac were placed under the direct supervision of the federal government. In a month time the index registered a cumulative decrease of 30%.

Table 4: Relative difference in Sep-2008

Date	$\frac{EMA_{16}(t) - EMA_{60}(t)}{P(t)}$
9/2/2008	0.47%
9/3/2008	0.29%
9/4/2008	-0.14%
9/5/2008	-0.54%
9/8/2008	-0.81%
9/9/2008	-1.30%
9/10/2008	-1.61%

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