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A Statistic Method for the Prediction of the Succession of Bear and Bull Stock Market

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***Abstract:** In this paper, we define an innovative method for predicting the stochastic behavior of the Bull and Bear periods of the stock market. The direct study of the prediction of possible Bull and Bear markets is a different and new approach about the analysis of stock markets. Our work is based on the collection of 40 years of data from the Italian stock market. The proposed solution is defined using the statistical analysis of the Bear and Bull Stock markets and it includes a criterion for statistically generating the most probable values of the next Bear and Bull markets, as well as especially the lengths of the time intervals corresponding to these market situations. We defined a new system for a stock market price trend prediction, where the trend of the succession of Bull and Bear markets can be described by a probability density function given by a Gaussian distribution. Furthermore, we considered the inverses of the relative time intervals as a measure of the speed with which the phenomenon of the Bear market (or, equivalently, the Bull market) develops in that interval of time and therefore, ultimately, it can represent a first statistical weight of the single percentage variation. Again, the time intervals of the individual Bear and Bull market periods are considered, calculated from 01/01/1973. This is based on the hypothesis that a secondary factor of probability is the temporal distance of the event that has already occurred. In this paper, we conduct a comprehensive evaluation of more frequently used statistical methods for evaluating Stock markets, highlighting the novelty of the described method. Simulation results show the ability of the method to define a statistical prediction of the next Bull and Bear markets.*

***Keywords**: Gaussian Distribution, Interpolation, Statistic Method, Stock Market.*

I. INTRODUCTION

Stocks are the shares of a firm. The stock exchange is a legal framework in which a person or group can buy and sell such shares systematically. The stock market is the hub of both sellers and buyers of stock.

The stock market has an important contribution to the rapidly growing world economy. The fluctuation in the stock market can have a significant influence on people and the entire economy. Stock market is one of the best alternatives for many business firms for further expansion.

The main objective of investors is motivated by the desire for capital appreciation. Generally, the firms, making more profit, provide a greater return to the investors than those firms making less profit. There are different reasons that influence the overall trend of stock markets such as political and economic situations, natural disasters, poor-corporate governance, and differing policy of the governing company.

The decision of choosing the most beneficial options in the stock market relies on how well a person is informed in the stock analysis. This is the reason it is important to identify the statistical models and their analysis. The statistical models allow for forecasting the share price movement of stocks. The arbitrary fluctuation of share prices causes the uniform distribution of market information. This inherent stochastic behavior of the stock market makes the forecast of possible states of the market more sophisticated. However, there are various statistical models to study the phenomena of stock behavior. For example, the Brownian motion model predicts the stock market using past information.

Initially, models with incomplete information have been investigated by Dothan and Feldman [1] using dynamic programming methods in linear Gaussian filtering.

Many models were used to predict stock executions such as the "exponential moving average" (EMA) and the "head and shoulders" methods. However, many of the forecast models require a stationary input time series. In reality, financial time series are often nonstationary, thus nonstationary time series models are needed. Auto-regression models have been modified by adding time-dependent variables to adapt to the non-stationarity of time series. Some recent papers using these models are [2]-[3]-[4]-[5]-[6]-[7]-[8]-[9].

Again, in the paper [10], the authors developed a method based on a Neural Network Model. Instead, in the paper [11], the authors developed a different method based on a stock price trend prediction model based on long short-term memory (LSTM).

A different approach to the statistical study of stock markets takes place through the Hidden Markov Model (HMM) method. It can be considered a tool to deal with time series problems. It is not affected by whether the data is linear or not when analyzing market conditions and the transition law between these states. Some very recent works regarding the Hidden Markov Model are [12]-[13]-[14]-[15].

In recent years some authors have tried to introduce a quantum theory for financial markets. The latest papers can be cited in this regard are [16]-[17]-[18]-[19]. The stocks have always been traded at certain prices, which, from the point of view of quantum mechanics, present corpuscular property. Meanwhile, the stock prices fluctuate in the market, which presents the wave property. Due to this wave-particle dualism, they suppose the micro-scale stock is a quantum system.

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We will follow a different approach. In fact, we believe that a fundamental point in the study of stock markets is given by the ability to predict when a Bear market will occur, i.e. that market phase characterized by a progressive decrease in the prices of financial assets and by pessimistic expectations. As a consequence, predict when a Bull market will occur, i.e. a market characterized by a more or less rapid increase in prices. Being able to establish in advance, with a good approximation, the beginning of a bear market period is, clearly, the fundamental factor for selling the stocks in advance and in a convenient way in order to be able to buy them when this is approximately over. In a simplified way, it can be said that the "ability to make money with the stock markets" is essentially given by the ability to predict the phases of the bear market.

We will use a statistical method deriving in part from those described in two previous works ([20] and [21]) by the author.

In this paper, we consider a financial market where we are going to define the successive max and min points of the statistical curve of the market analyzed (FTSE MIB Italia), corresponding to price variations over time of more than 20% (generally accepted definition for bear and bull markets). Such, that is, to be defined as bear or bull markets, depending on whether prices are falling or rising.

We assume that the unobservable and future processes are modeled by a stochastic process. Precisely, we define a Gaussian trend of the probability distribution in order to obtain the values of the predictor variables. Based on the defined method, a criterion is established for statistically generating the most probable values of the next Bear and Bull markets, as well as above all the lengths of the time intervals corresponding to these market situations. The paper is organized as follows: In Section II, we describe the model and formulate the method used. In Section III, we illustrate our results with graphs describing expected market trends. Finally, in Section IV, we give our conclusions.

II. DESCRIPTION OF THE STATISTICS METHOD

We will describe the statistical method defined to obtain the values of the predictive variables relating to the peaks corresponding to the Bear market and the Bull market and the time intervals in which these transitions take place. First, let's define a Bear market and a Bull market. A Bull market is a period of time in financial markets when the price of an asset or security rises continuously. The commonly accepted definition of a Bull market is when stock prices rise by 20% or more. While Bull markets are fueled by optimism, Bear markets, which occur when stock prices fall 20% or more for a sustained period of time, are just the opposite. Bull markets are generally powered by economic strength, whereas bear markets often occur in periods of economic slowdown and higher unemployment.

The method we have defined for predicting Bull and Bear markets is based on the following steps:

1. The data of the Bull and Bear markets are determined, using the case relating to the Global Comit Index for the Italy Stock Market which has been available since the beginning of 1973, thus resulting in the historically longest index available on this market. The inferred data for the Bull and Bear markets have been included in Table I, shown below.
2. We hypothesized that the trend of the succession of bull and bear markets can be described by a probability density function given by a Gaussian distribution defined by (1). The fundamental characteristics of this Gaussian curve are determined in the following points.

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}\right) \qquad (1)$$

where μ is the expected value and σ is the variance of the Gaussian function.

Table I: Global Comit Index - Bear and Bull Markets and corresponding Corrections Since 1973

Pos.	Peak Date (mm/dd/yyyy)	Trough Date (mm/dd/yyyy)	Initial Price	Final Price	Percent. Variation	Number of working Days
1	01/02/1973	06/19/1973	111.35	162.21	45,6	121
2	06/19/1973	08/07/1973	162.21	117.51	-27,5	14
3	08/07/1973	04/18/1974	117.51	154.25	31,2	183
4	04/18/1974	12/20/1974	154.25	85.97	-44,2	177
5	12/20/1974	03/11/1975	85.97	107.63	25,2	58
6	03/11/1975	10/17/1975	107.63	75.41	-29,8	159
7	10/17/1975	07/20/1976	75.41	88.12	16,8	198
8	07/20/1976	11/10/1976	88.12	64.93	-26,3	82
9	11/10/1976	12/07/1976	64.93	75.76	16,6	20
10	12/07/1976	06/16/1977	75.76	58.55	-22,5	138
11	06/16/1977	09/21/1978	58.55	84.03	43,5	331

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12	09/21/1978	12/19/1978	84.03	67.50	-19,6	64
13	12/19/1978	06/03/1981	67.50	292.03	332,6	642
14	06/03/1981	10/20/1981	292.03	172.22	-41	100
15	10/20/1981	03/19/1982	172.22	212.66	23,4	109
16	03/19/1982	07/22/1982	212.66	147.23	-30,7	90
17	07/22/1982	05/20/1986	147.23	908.19	516,8	999
18	05/20/1986	06/20/1986	908.19	653.83	-28	24
19	06/20/1986	06/16/1987	653.83	719.03	9,9	258
20	06/16/1987	02/10/1988	719.03	427.51	-40,5	172
21	02/10/1988	06/14/1990	427.51	763.53	78,6	612
22	06/14/1990	01/29/1991	763.53	486.25	-36,3	164
23	01/29/1991	06/20/1991	486.25	612.32	25,9	103
24	06/20/1991	12/10/1991	612.32	482.89	-21,1	124
25	12/10/1991	02/25/1992	482.89	545.03	12,8	56
26	02/25/1992	09/07/1992	545.03	361.52	-33,6	140
27	09/07/1992	05/11/1994	361.52	817.17	126	438
28	05/11/1994	12/13/1994	817.17	581.64	-28,8	155
29	12/13/1994	07/20/1998	581.64	1623.52	179,1	940
30	07/20/1998	10/09/1998	1623.52	1063.50	-34,5	60
31	10/09/1998	11/15/2000	1063.50	2095.95	97	549
32	11/15/2000	09/21/2001	2095.95	1082.91	-48,3	223
33	09/21/2001	04/17/2002	1082.91	1513.03	39,7	149
34	04/17/2002	07/24/2002	1513.03	1077.76	-28,7	71
35	07/24/2002	08/27/2002	1077.76	1226.88	13,8	25
36	08/27/2002	10/09/2002	1226.88	974.37	-20,5	11
37	10/09/2002	05/18/2007	974.37	2149.12	120,5	1203
38	05/18/2007	03/09/2009	2149.12	655.07	-69,5	472
39	03/09/2009	05/02/2011	655.07	1153.75	76,1	561
40	05/02/2011	09/12/2011	1153.75	744.54	-35,4	96
41	09/12/2011	12/01/2015	744.54	1273.81	71	1102
42	12/01/2015	06/27/2016	1273.81	916.83	-28	150
43	06/27/2016	01/29/2018	916.83	1394.58	52,1	416
44	01/29/2018	12/27/2018	1394.58	1073.50	-23	239
45	12/27/2018	02/19/2020	1073.50	1479.33	37,8	300
46	02/19/2020	03/23/2020	1479.33	917.29	-38	24
47	03/23/2020	01/05/2022	917.29	1654.74	80,3	468
48	01/05/2022	09/29/2022	1654.74	1200.69	-27,4	192

[a] Variations with a negative sign correspond to Bear markets, with positive sign to Bull markets

3. By adding the working time intervals Δt_i of the various periods reported in Table I, the time distance t_i from the origin of the times is determined, which is set on 01/01/1973.
4. The inverses $(1/\Delta t_i)$ of the working time intervals Δt_i are determined. These inverses can be considered a measure of the speed with which the phenomenon of the Bear market (or, equivalently, the Bull market) develops in that interval of time and, therefore, ultimately, it can represent the first statistical weight of the single percentage variation (ΔV_i) in that time interval with respect to the entire Gaussian probability distribution.
5. The normalized values ϕ_i of the primary weights are obtained, defined as follows:

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$$\phi_i \equiv \left(1/\Delta t_i\right)_{norm} \triangleq \left(1/\Delta t_i\right)/\sum_i \left(1/\Delta t_i\right) \qquad (2)$$

6. Subsequently, the time intervals of the individual Bear and Bull market periods are considered, calculated from the origin of the time axis, i.e. from 01/01/1973. This is based on the hypothesis that a secondary factor of probability is the temporal distance of the event that has already occurred, i.e. the more distant the phenomenon, the more likely it is to happen. Therefore, with this assumption, we make the chain of events non-Markovian. However, in order not to make this secondary factor too important, we consider it a logarithmic power, thus smoothing out the difference between the extreme values. Thus, starting from the time distances t_i from the origin of the times of the single events, we define the normalized coefficients Υ_i of the secondary weights as:

$$\gamma_i \equiv \left[1/(\ln t_i)^n\right]_{norm} \triangleq \left[1/(\ln t_i)^n\right]/\sum_i \left[1/(\ln t_i)^n\right] \qquad (3)$$

7. The overall normalized coefficients are determined $[\phi_i\Upsilon_i]$, for each time interval Δt_i, in the following way:

$$\left[\phi_i\gamma_i\right]_{norm} \triangleq \phi_i\, \gamma_i / \sum_i \phi_i\gamma_i \qquad (4)$$

8. Based on overall normalized coefficients $[\phi_i\Upsilon_i]$ t is possible to define the probability density given by a Gaussian distribution. For this purpose, since ΔV_i is the single percentage variation in the time interval Δt_i, we have to determine based on (1) the expected value μ and the variance σ of the Gaussian function:

$$\mu \triangleq \frac{\sum_i \left[\phi_i\gamma_i\right]_{norm} \Delta V_i}{n} \qquad (5)$$

$$\sigma^2 \triangleq \frac{\sum_i \left\{\left[\left(\phi_i\gamma_i\right)_{norm}\left(\Delta V_i\right)\right]-\mu\right\}^2}{n} \qquad (6)$$

9. We will define 2 Gaussian distributions, relating respectively to the Bull and Bear markets, i.e. in practice relating to the positive percentage changes $(\Delta V_i)_p$ and negative percentage changes $(\Delta V_i)_n$ in subsequent time periods. So we will have:

$$\mu_p \triangleq \frac{\sum_{i,p} \left\{\left[\phi_i\gamma_i\right]_{norm,p} \Delta V_{i,p}\right\}}{n_p} \qquad (7)$$

$$\sigma_p^2 \triangleq \frac{\sum_{i,p} \left\{\left[\left(\phi_i\gamma_i\right)_{norm,p}\left(\Delta V_{i,p}\right)\right]-\mu_p\right\}^2}{n_p} \qquad (8)$$

$$\mu_n \triangleq \frac{\sum_{i,n} \left\{\left[\phi_i\gamma_i\right]_{norm,n} \Delta V_{i,n}\right\}}{n_n} \qquad (9)$$

$$\sigma_n^2 \triangleq \frac{\sum_{i,n} \left\{\left[\left(\phi_i\gamma_i\right)_{norm,n}\left(\Delta V_{i,n}\right)\right]-\mu_n\right\}^2}{n_n} \qquad (10)$$

10. The two Gaussian distributions, relating to the Positive Variations (Bull market) and the Negative Variations (Bear market), will therefore be given, respectively, based on (1) by:

$$g_p(x_{i,p}) = \frac{1}{\sigma_p\sqrt{2\pi}} \exp\left(-\frac{1}{2}\frac{(x_{i,p}-\mu_p)^2}{\sigma_p^2}\right) \qquad (11)$$

$$g_n(x_{i,n}) = \frac{1}{\sigma_n\sqrt{2\pi}} \exp\left(-\frac{1}{2}\frac{(x_{i,n}-\mu_n)^2}{\sigma_n^2}\right) \qquad (12)$$

being:

$$x_{i,p} \triangleq \left(\phi_i\gamma_i\right)_{norm,p}\left(\Delta V_{i,p}\right) \qquad (13)$$

$$x_{i,n} \triangleq \left(\phi_i\gamma_i\right)_{norm,n}\left(\Delta V_{i,n}\right) \qquad (14)$$

11. At this point, we have to define the procedure for obtaining the predictive values of the variables considered. With this aim, we define a pseudo-random number generator, using an algorithm based on Linear Congruential Generators (LCG). To do this, we will construct two one-dimensional arrays of data whose elements are given respectively by $g_p(x_{i,p})$ and by $g_n(x_{i,n})$. Based on their statistical weight, each of these elements will be repeated several times in the one-dimensional matrix, to reproduce the weight of the element itself. Thanks to the LCG algorithm, starting from an initial value x_0 called seed, the values of the pseudo-random sequence are defined. Through this sequence, we obtain the successive predictive values of the variables $x_{i,p}$ and $x_{i,n}$. From these variables, then the corresponding ones are calculated, through (11) and (12), $g_p(x_{i,p})$ and $g_n(x_{i,n})$, as well as the corresponding Δt_i.
12. Finally, we generate the linear or cubic spline interpolation curves of the sequence of maxima and minima relating to the successive Bull and Bear markets, in order to represent the succession of the same markets over time.

III. RESULT AND DISCUSSION

To study the trend of the Bull and Bear markets in practice and determine the predictive effects relating to them through statistical analysis, the case study relating to the Global Comit Index for the Italy Stock Market which has been available since the beginning of 1973 is used. From the data of this Index, we obtain those defined in Table I, i.e. the succession of Bear and Bull Markets, the corresponding Corrections Since 1973 and the corresponding working time intervals.

Using the method and process described in detail in section II above for this data, we can derive the sequence of predictive values for Bull and Bear market situations. As written in Section II, starting from an initial value x0 called the seed in (13) and (14), the subsequent predictive values of the variables are defined $x_{i,p}$ and $x_{i,n}$. of the sequence pseudo-random.

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In the first instance, the chosen seed or root x_0 was 511 on a one-dimensional array of 811 elements. Based on the repetitions of the values in the one-dimensional matrix, it corresponds to position 21 in Table I for the Bull market interval. The next value obtained thanks to the LCG algorithm, i.e. 665, allows us to obtain position 34 in Table I for the Bear market interval.

Thanks to the LCG algorithm, the following values 240, 739, and 462 are always obtained on the one-dimensional matrix of 811 elements. They correspond respectively to positions 7, 36, and 17 in Table I.

To obtain the corresponding predictive value of Δti the expression is used:

$$\Delta t_i \triangleq \left(\Delta t_{psrand} + \Delta t_m\right)/2 \tag{15}$$

where Δt_{psrand} is the Δt_i of the determinate element Table I by the pseudo-random algorithm LCG and Δt_m is the determinate medium Δt, respectively, for the Bull and Bear market intervals.

To calculate the Peak values of the Bull and Bear markets, respectively peak values of Max and Min, we will use the following expression:

$$\Delta V_i \triangleq \left[\left(\phi_i \gamma_i\right)_{norm}\left(\Delta V_{psrand}\right)\right] - \sigma_m \tag{16}$$

where ΔV_{psrand} is the ΔV_i of the element in Table I determined by the LCG pseudo-random algorithm and σ_i is the standard deviation obtained by (8) and (10), respectively, for the Bull and Bear markets.

In this way an iterative procedure was built which adds new rows to the previous rows of Table I, obtaining the new Peak values and the new Δt_i through which to calculate the subsequent predictive values.

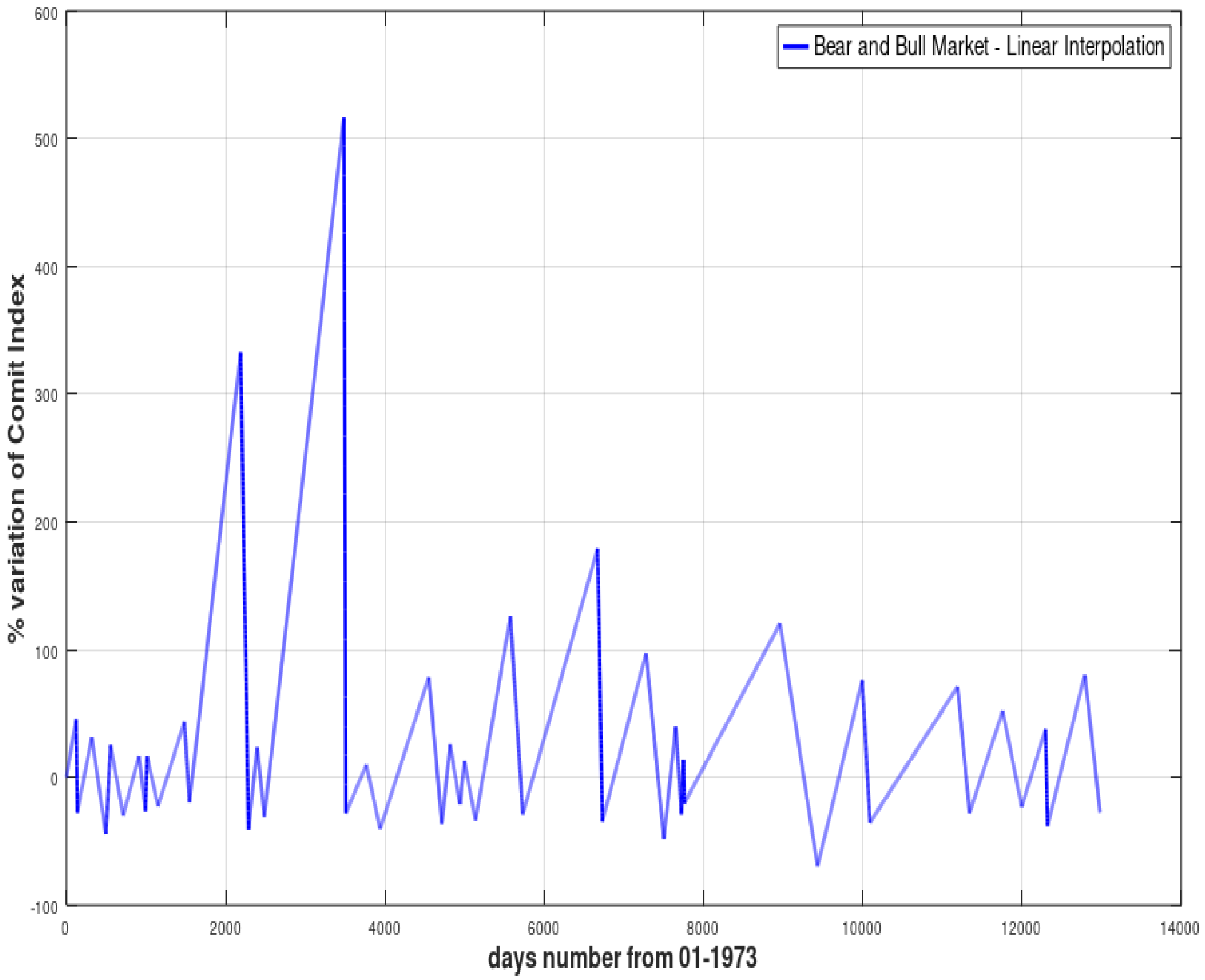

Fig. 1.Bear and Bull Italy Market - Linear Interpolation – Comit Index from 1973 to Nov. 2022

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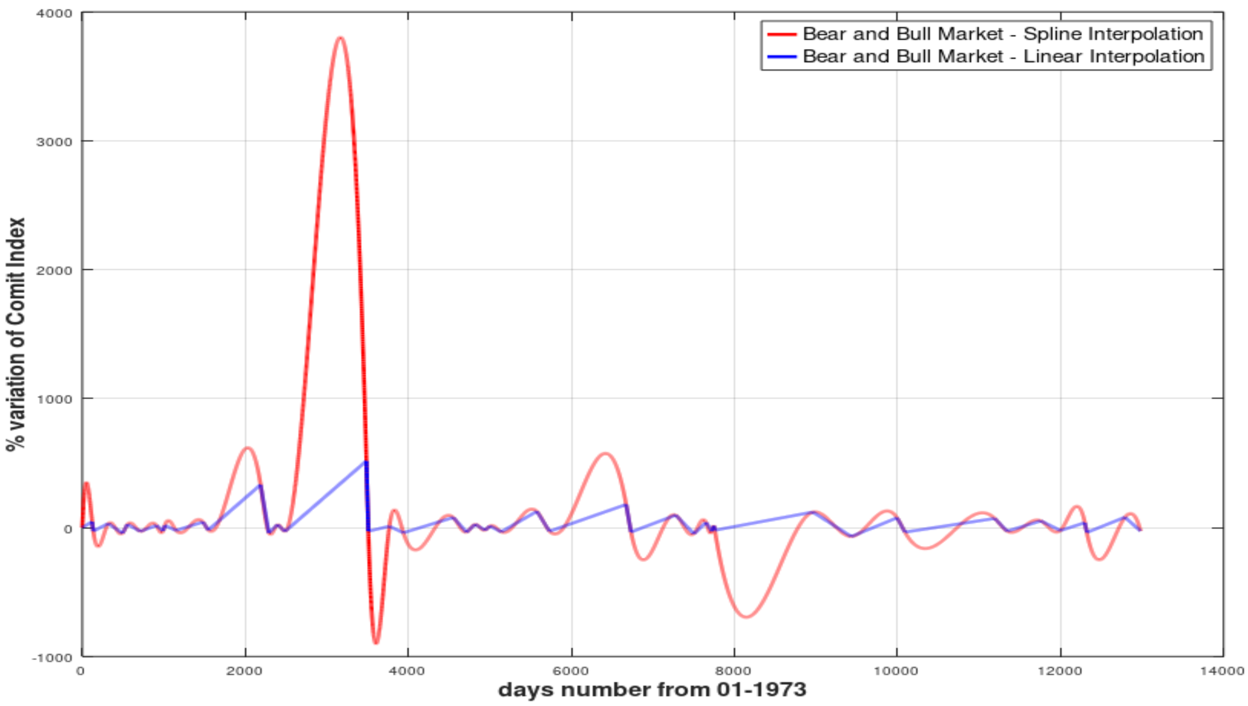

Fig. 2. Bear and Bull Italy Market - Linear and Spline Interpolation – Comit Index from 1973 to Nov. 2022

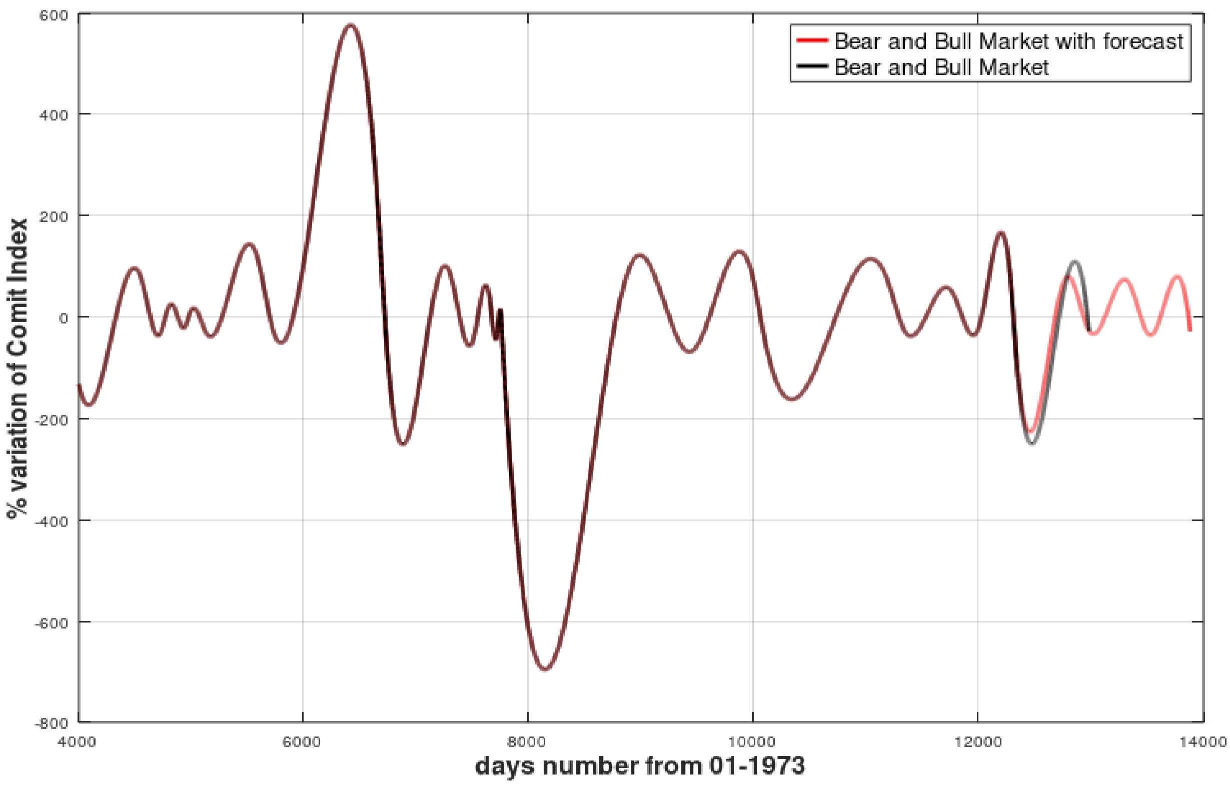

Fig. 3. Bear and Bull Italy Market - Spline Interpolation – Comit Index from 1973 to Nov. 2022 – Predictive forecast

Using GNU Octave version 5.1.0., we have generated some explanatory graphics of the implemented method. Fig.1 gives the Linear interpolation of the subsequent Bull and Bear markets, obtained by the Comit Index from 1973 to Nov. 2022. In this figure, we see, well highlighted, the trend of the Linear Interpolation relating to the Bear and Bull Italy Market, taken from the Comit Index from 1973 to Nov. 2022. It defines the relative Max. and Min., taken from Table I.

Fig.2 instead highlights the differences between the trend of the Linear Interpolation and the trend of the Spline cubic Interpolation. It is evident that, due to the interpolation method, the values of cubic spline are much larger than those of linear interpolation. However, the latter is more realistic considering the max and min values.

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Fig.3 represents probably the most important graph among those presented. This figure, in fact, gives the spline interpolation of the subsequent Bull and Bear markets, both for the past time and for the forecast markets. In particular, the predictive trend of the next Bull and Bear markets, obtained as described in Section II and in this Section III, is highlighted with a red line.

IV. CONCLUSION

In this paper, we investigated the Bear and Bull Stock markets and proposed a statistic to generate the most probable values of the next Bear and Bull markets. Furthermore, with our statistical method, we generated the lengths of the time intervals corresponding to these market situations. We relied on 40 years of data from the Italian stock market. An implementation of the method and the most relevant results are described. Possible future developments of this work concern the study of possible alternative methods to obtain the successive statistical max and min.

DECLARATION

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Conflicts of Interest/ Competing Interests	No conflicts of interest to the best of our knowledge.
Ethical Approval and Consent to Participate	No, the article does not require ethical approval and consent to participate with evidence.
Availability of Data and Material/ Data Access Statement	Not relevant.
Authors Contributions	I am only the sole author of the article.

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