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Developing Timing Strategies in the Resilience of the Iranian Capital Market*

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Abstract

One of the important sectors of the economy of any country is their capital market and this sector, as one of the subsets of economy in the event of crisis and external shocks and instability in the economy is affected, which makes evident the need to pay attention to the stability of this sector and, more importantly, to increase its resilience. The 2008 global financial crisis affected all asset classes, making diversity in crisis and recession an inefficient mechanism for risk management. Applying the timing approach in investment, it is possible to have a favorable encounter with high-risk assets such as stocks. By developing Exponential Moving Average (EMA) timing strategies, this study commits to take an effective step in protecting the investment portfolio against significant declines in turbulent times and financial crises and reducing stock investment by creating a cash position. It therefore seeks to test the effectiveness of K-Means clustering in the development of a market timing strategy (i.e. EMA) that intends to provide early signals to protect securities in turbulent times. The specified timing strategies were tested on the total index of the stock exchange during the period 2013-2019. The results indicate that the optimal EMA strategy will have a better performance using the K-Mean clustering when the trend (the time series of the index) has structural breaks and the results from the predictions obtained from this tool can be closer to the reality. Also using the clustering method, the sensitivity of this market timing tool in a situation where the market trend is experiencing severe economic fluctuations and shocks has improved and enjoyed more resistance.

Keywords

Exponential Moving Average, K-Mean Clustering, Market Timing ,Stock Index Resilience, Structural Break.

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1. Introduction

Resilience is a well-known issue in the fields of natural sciences, psychology, and engineering, as well as the management of urban and organizational crises. But in recent years, especially after the 2008 financial crisis, the issue of economic resilience attracted the attention of the elites of this field. The 2008 global financial crisis affected all asset classes, making diversity in crisis and recession an inefficient mechanism for risk management (Haung Hesiang et al., 2012).

The risk management approach does not work for all financial risks, in today's turbulent and uncertain world, economic and social systems face many risks that have low predictability and human knowledge about their effects and consequences is low. This type of risks due to their exogenous nature are beyond the individual's effective capacity and control, so no group or area are safe from this type of risks (Chavoshi and Kabirian, 2019).

The capital market, as a part of the country's overall economy, is also affected by it and affects it, and in recent years, adverse economic risks have affected the capital market (Manzoor and Mostafapour, 2013). One of the ways to reduce the effects of shocks and Environmental threats faced by organizations and communities are the issue of resilience. Masten (2018) considers resilience to be the system's ability to successfully adapt to fundamental environmental challenges that threaten its performance, sustainability and development.

The collapse of the bond, credit and stock markets, significant decline in indices and falling exchange rates are among the signs of financial crises. Financial crisis can lead to collapse of international markets, collapse of stock markets, financial bubbles, monetary crisis, and foreign debt, so that it eventually results in a sudden decline in economic activities and creates a potential for economic recession (Rahimi Baghi et al., 2018). The 2008 financial crisis and the subsequent great recession are still fresh in the memories of many investors. People observed that their securities lost 30% or more of their value. Instead of taking rational action in severe bear markets, many people overreact, causing the recession to continue. And in this situation, the lack of an investment strategy and blindly following the Buy and Hold (BH) approach leads to bankruptcy and loss of total capital because the investors with the BH strategy are not able to save their portfolio from severe market collapses due to their liquidity constraints (Haung Hesiang et al., 2012). Market timing is an active trading strategy that aims to go beyond the Buy and Hold strategy. Investors use technical analysis tools to predict the direction of markets and decide when to enter or exit markets or to transfer between different classes of assets (Yafeng Quinn, 2020). The goal of a successful market timing system is first to maintain the portfolio capital and then to escape major market downturns and falls; in other words, the goal is to have a good timing strategy, to trade during uptrends, and to take cash positions during bear markets (Sharp, 1975: 60) in order to perform better than the risk-adjusted buy and hold portfolios do and to help the investor in making the right decisions by determining the time of buying and selling securities (Bashirpour et al., 2016).

During severe economic shocks and recessions, all assets experience a significant decline, and according to Faber's research in 2009, using the Buy and Hold strategy for any reason during a global financial crisis is a completely unwise attempt because the benefits of the portfolio diversification that Markowitz (1996) talked about become disappeared. Therefore, the need to develop strategies that perform better than the BH strategy does in declining market trends and economic crises that show a negative return index is increasingly felt. Also by modeling structural equations concluded that the occurrence of shocks such as sanctions and their impact on the capital market, Chavoshi and Kabirian (2020) in their research on the resilience model of the Iranian capital market show the vulnerability of this market and the resilience of the market capital; so, the need to find a solution to improve its resilience to shocks is felt.

Therefore, this study seeks to develop a moving average EMA market timing strategy that, by helping to reduce the equity investment and create a cash position, maintains the investors and mutual funds'

returns against losses due to recessions, crises, and turbulent conditions and increases their economic resilience, and based on the expected market trends, they can potentially be more resilient than traditional BH strategies (Haung Hesiang et al., 2012). So far, no research has been done on increasing the resilience the timing tools to escape from severe recessions and protect the portfolio in Iran. Therefore, considering the necessity to discuss the economic resilience in research literature and the importance of increasing the resilience of the economy and market to shocks and foreign threats, this study seeks to increase the resilience of the moving average as a well-known tool in the market timing. Thus, this paper attempts to test the effectiveness of the K-Means market clustering method on the performance of the EMA moving average market timing strategy, which intends to provide early signals to protect securities in turbulent times. We use the Exponential Moving Average (EMA) and the K-Means clustering test for timing the market. Therefore, in this research, we will seek to cluster and analyze the market behavior using data mining techniques. The K-Means methodology has been used for market clustering. Accordingly, in each cluster, the clusters will be evaluated and identified in order to create a better understanding of the behavior of the moving average during economic shocks and structural breaks. The ultimate goal of this research is to develop successful market timing strategies that maintain the portfolio value of the total index of the stock market without creating a significant pull in its upside potential when the market returns back during a significant recession and turbulent economic conditions.

2. Theoretical Basics and a Review of Research Background

Since the 1980s, much research has been done on market timing and generally focus on the potential gains and accuracy required by market timing strategies (Sharp, 1975; Chouvain, Woodward and Thau (1987); Clark, Fitzgerald, Brent and Statman (1989); Kaster (1990); Boyer and Dahlquist (2001)). They showed that incorrect market timing leads to exposure to larger losses with irreparable costs in transactions. Another series of other studies (Schilling (1992); Resnick and Shoesmith (2002); Ang and Bekaert (2004); Estrada (2008)) are about market timing and developing centralized market timing strategies in order to make more effective use of transfers between asset classes. And almost all of these researchers have concluded that savings from avoiding the bear market (recession) can be more profitable than the opportunity cost of losing the bull market (upside).

Between 2000 and 2010, we faced extensive research on the technical analysis of financial markets. This interest arose because it was found that using certain tools and following business rules would help investors to avoid large losses during the intense bear markets that occurred during the 2000s. One of the timing strategies to follow the trend is the moving average law. In most cases, one uses the Simple Moving Average (SMA) rule, which signals a change in the position of securities (transfer into cash) and vice versa when the price is higher or lower than the monthly average trend line.

Hudson et al. (1996) in their study entitled "The Application of Simple Technical Trading Rules to UK Stock Prices" examined whether the application of technical analysis can lead to additional returns. They conducted their surveys on the London Stock Exchange Index (FT30) for the years 1935 to 1994. The conclusion was that although the use of these rules leads to the dimensions of predictive power in the data of the FT30 Index of the London Stock Exchange, but it does not lead to greater returns on the Buy and Hold method. The final result of Hudson and Brooke's research is that the technical trading rules are profitable, or in other words, predictable if the long-term data sets are considered; also if we consider transaction costs, the return on the Buy and Hold method becomes greater than that on the technical method. Hudson, unlike Brooke, concluded that technical strategies have nothing to do with market efficiency.

Faber (2009) examined the maximum decline in all asset classes, including US stocks, the EAFE stocks,

commodities, and Real Estate Investment Trust (REIT) from 1973 to 2008, with the results showing that all asset classes have lost 40% to 60% of their value – with the exception of US government bonds, which have lost about 20% of their value. In another study, he tested the ability of a moving average timing model to protect investment and create a cash position during crises. He applied timing strategy to five common indicators: the S&P 500 Index, the MSCI EAFE Index, the Goldman Sachs Commodity Index (GSCI), the National Association for Real Estate Investment Trust (NAREIT), and the 10-year US Treasury Index from 1900 to 2008; showed that when the level of the monthly index is higher than the 200-day moving average and vice versa, it indicates the position of the index and the signals of the moving average trading system are issued according to the position of the moving average line ratio. The results show that during crises, investor uses the timing strategy to face less losses and large profits and to more profits and small losses. In other words, using this strategy, the investment portfolio risk is very smaller during financial crises than when other strategies are used; and timing strategies such as moving averages over long periods of time have significantly less volatility and decline. Faber (2009) concluded that the moving average trading system is a more effective mechanism to prevent the impact of financial market catastrophes because it achieves similar returns on stocks as fluctuations and bonds fall.

The empirical literature shows that market timing strategies, which involve frequent shifts between bonds and cash based on short-term forecasts, require high forecast accuracy to justify their trading costs. Motivated by this argument, a 2012 study by the Hung et al. developed portfolio-based timing strategies aimed at maintaining stock portfolio values over long periods of uncertainty in order to reduce bad systemic effects. The benefits of avoiding economic and structural shocks often outweigh the benefits of engaging in the bull market. They conducted their research on the resilience of the global index using market timing strategies during financial crises. They tested two moving average EMA strategies and a filtering law strategy based on the stock thresholds (drawdown thresholds (DD)) and drawup thresholds (DU) on the Morgan Stanley Capital International (MSCI World) return index since its inception from 1997 to 2008 in order to test the effectiveness of the two market timing strategies aimed at providing early signals to protect securities in turbulent times; ratios that are higher than the global unprotected Sharpe ratio, MSCI. And a comparison of the historical risk return characteristics shows that the exponential moving average strategy in capital protection is more accurate than the other strategies studied in the research are. As with all market timing strategies, the signals provided by the mechanism for protecting from real economic events are sent later. Therefore, market timing strategies are more effective for long-term recessions.

Many other studies on market timing using moving average method have been done in the world by Glabadanidis, P and Zakamulin, V, and McAleer, M Laurila, H., Ilomäki, J between 2014 and 2020. For example, Jukka Ilomäki et al. (2018) used the Simple Moving Average (MA) rule to determine when to buy and sell stocks and change the situation to a risk-free investment position. The main question was: when using the moving average method, to what extent performance and efficiency were affected? The experimental results show that the return fluctuations are about 30% less than those in the BH strategy, but when the moving average gives fewer signals to change position, the average return is close to the BH return. And when we accidentally invest half in stock markets and half in securities at a risk-free rate, a 30% reduction in return fluctuations can be seen. This is a sign of a reduction in investment risk when using moving average.

Also, a lot of research has been done on resilience in the Iranian economy, but researches on resilience in the Tehran Stock Exchange index and market timing are little, and so far no research has been done on resilience in the stock market using a market timing approach. But a lot of research has been done on comparing the moving average method and other

technical analysis tools to get a higher return on the BH strategy.

In 2020, by the structural equation modeling, Chavoshi and Kabirian conducted a research on the resilience pattern of the Iranian capital market. The occurrence of shocks such as sanctions and their effect on the capital market indicates the vulnerability and the resilience of the capital market as well as the need to improve their resilience to such shocks. In this study, the resilience of the Iranian capital market and the development of a model for it have been discussed. First, a theoretical model was presented and using the structural equation modeling method, the hypotheses were tested and the proposed model was matched with the data obtained from a survey on the experts. The model evaluation shows that resilience has a significant relationship with financial institutions, financial instruments, regulators, laws and regulations, markets, and issuers, and the positive effect of financial institutions and the negative effect of financial instruments are significant. On the other hand, it was shown that capital market resilience has nothing to do with the environment around the capital market. Finally, each of the findings was interpreted and appropriate suggestions were extracted from them. If the Iranian capital market has resilience characteristics in terms of institutions, instruments, regulatory bodies, laws and regulations, markets, and issuers, then it can be said that the entire capital market has enough resilience to environmental risks and in the event of a crisis, it is able to properly exit the imbalance state and change in the face of long-term environmental trends.

Heibati and Rahnama Roodposhti (2020) investigated the relationship between the two stock pricing approaches (technical and fundamental analyses) in the Tehran Stock Exchange. The technical strategy is calculated based on the dual moving average indices, the exponential moving average index, the Relative Strength Index (RSI), the cash flow index, and the Moving Average Convergence Divergence (MACD) index and the asset pricing model is used in the fundamental strategy. The results from the hypotheses test in the 5-year period (2004 to 2008) show that there is a positive and significant relationship between the calculated return (by 5 technical indicators) and the real return as well as between the returns obtained from the asset pricing model and the real returns of the market. Other results of the test show that there is a positive and significant relationship between the expected return of the dual moving average indices, relative strength index, and cash flow index and the return of the asset pricing model, but there is no significant relationship between the return of the exponential moving average and the convergence divergence moving average index and the return of the asset pricing model.

Pourzamani and Rezvani Aghdam (2015) investigated the effectiveness of technical strategies of the Exponential Moving Average (EMA) strategies and the Relative Strength Index (RSI) by the BH method for buying stocks. Buying opportunities were extracted based on daily (short-term) and weekly (medium-term) periods for 16 investment companies in the Tehran Stock Exchange in the three years 2011 to 2013 and compared with the data obtained by the BH method. The results showed that in highly bullish periods (2013), the technical strategies do not have the necessary efficiency, but in periods with a balanced market trend, the technical strategies for buying stocks are more effective. In 2012, they also explained the stock trading methods investigated two methods of stock market forecasting methods (the Buy and Hold method and the simple moving average method) and the results show that in the short-term investment period, the average return of the BH method is higher than that of the moving average method.

In 2010, Taghavi et al. conducted a study with the aim of investigating the effect of the Western financial crisis on the Tehran stock exchange. The results of this study showed that firstly, the Western financial crisis has not affected the performance of the Tehran Stock Exchange and, secondly, the persistency of the fluctuations in this period has been low.

Subsequently, in 2017, Rahimi Baghi et al. conducted a study on determining the occurrence dates of the financial crises in the Tehran Stock Exchange in a direct way with an emphasis on the inflation, and the

occurrence dates of the financial crises in the Tehran Stock Exchange were determined in a direct way within the time interval between 2001 and 2017. The results showed that in the mentioned time period, the Tehran Stock Exchange has experienced during the two periods of the financial crises during the years 2008 to 2015. Also, after comparing the timing of the mentioned crises with the crises related to the eight European countries and the United States, it was found that only a part of the time period of the first crisis of the Tehran Stock Exchange is shared with the crisis time periods in these countries and the second crisis has no shared crisis time period with any of them.

Then, in 2017, a research was conducted by Kiarash Mehrani et al. in the Tehran Stock Exchange on timing strategies. This study investigates the relationship between the market timing strategies and the surplus returns in the companies listed on the Tehran Stock Exchange. In this study, from the companies listed on the Tehran Stock Exchange for a period of five years from 2009 to 2014, 50 companies were selected and tested. The results showed that the timing strategies can generate surplus returns and show that the market timing based on the E/P strategy has a positive and significant relationship with the surplus market returns, so that as E/P increases, surplus returns increase.

Hassanzadeh et al. (2020) conducted a study on identifying and prioritizing the factors affecting the capital market resilience. In order to conduct the research, in the first stage, through reviewing the background and interviewing the financial experts, the main factors affecting the capital market resilience were identified. Subsequently, with the use of Binem and Dematel[1] nonparametric test, the main factors were screened and non-important factors were excluded.

Results. The main final factors are: structure and processes of the organization; attention to learning and teaching; information sharing; identification and analysis of shocks; next threats and risks; variety of designs and options available; technology acceptance rate; improvement and development.

Conclusion. Sub-factors of each of the main factors were identified. Finally, by applying the CODAS decision-making technique, the priority of sub-factors in each group of the main factors was determined. Finally, suggestions were made for the resilience of the capital market considering the priority of sub-factors.

3. Research Hypotheses

Given the diversity of timing methods that have taken place in the market, the question arises as to: how much the market timing using the EMA method along with the K-Means clustering method will be effective in increasing the resilience and improving its performance during significant downturns and turbulent economic conditions of the market?

In order to conduct tests to extract the necessary answers to the main research question, the research hypotheses are presented as follows:

Hypothesis 1. The resilience of the proposed timing method using the K-Means clustering during significant recessions is better than its initial state.

Hypothesis 2. The performance of the proposed timing strategy the research using the K-Means clustering method is better than that of the strategy used before the clustering during crises and severe shocks.

4. Research Methodology

Since the ultimate goal of this study is to develop successful market timing strategies for use in times of severe shocks and turbulent economic conditions, it is an applied research in terms of purpose. Also, in terms of data collection, the research is casual-comparative because it seeks to investigate the effect of the market clustering on the performance of the EMA timing strategy during significant recessions. In terms of data type, the study is quantitative. The data studied in this study are the daily prices of the total index of the stock exchange and are analyzed based on the information extracted from the stock exchange index. Persian and

Latin specialized articles and journals have been used to collect the information from the part of the research data that is related to the theoretical foundations of the research. For the other part of the research, i.e. the data, in addition to the library method and the information required to design and test the model, we referred to the trading archive on the Tehran Stock Exchange website (TSETMC) and extracted the information on the total stock index from 2003 to 2019. Also, the hypotheses were tested with the Eviews software.

4.1. Introducing models and Measuring Research Variables

In recent years, shocks and changes have led to disruption of Iran's economic and financial system. With the implementation of EU and US sanctions since 2006, a negative exogenous shock entered the country's financial and economic system (Manzoor and Mostafapour, 2013). In this study, we compare the capital protection-based timing strategy (EMA) between 2003 and 2019 with the conditions in which the structural breaks of the market were identified using the Bai-Perron test and the Hodrick-Prescott filter. Then using the K-Means clustering method, the index is smoothed and in each cluster the EMA is checked and eventually the performance of the EMA after clustering will be compared to the performance before clustering. In this comparison, in the both cases, the EMA strategy starts with investing 100% of its capital in the market portfolio in the total index. The resilience of the EMA to shocks will then be validated and the performance of the total performance of the EMA will be compared with its performance when the market is clustered.

Table 1 shows the descriptive statistics related to the time series of the data of the securities index in the period 2003 to 2019.

A comparison between the mean values and the standard deviation shows that the total index yield has fluctuated sharply over the period under study. The skewness coefficient also shows that the distribution of the data on the Tehran Stock Exchange index has a positive skewness, which is one of the accepted characteristics of the stock market indices. Also, the kurtosis coefficient is much higher than the kurtosis coefficient of the normal distribution, which is equal to 3, indicating that the distribution has higher peak sharpness than the normal distribution. The values of the skewness and kurtosis coefficients indicate a high deviation from the normal distribution, which is confirmed by the high Jarque-Bera statistic.

Table (1)Basic indicators of descriptive statistics

Total price index	Statistical index
TEPIX	
56233.03	Average
25094.31	Middle
555167.7	Maximom
5071.130	Minimum
76151.53	standard deviation
3.010945	Skewness
14.08102	Elongation
28967.36	Jarkbera statistics
0.000	probability level
4434	Number
2.46E+08	Total
2.53E+13	Total error squares

With a Buy and Hold strategy, they start by investing 100% of their capital in the market portfolio in the total index. By the end of the period, i.e. March 19, 2020, the total capital plus the return is converted into cash. As can be seen in the table above, the average of the total stock index during the period, i.e. March 20, 2003 to March 19, 2020 was equal to 56333.03, which shows a return of 562.33% of the buy and hold portfolio and a risk of 761.51% of the portfolio with respect to the variance of the index.

Examining the history of the data (trend of the total index of the stock market) in order to identify and determine the nature of a phenomenon is the first step in a principled modeling for the time-dependent data based on the past information of that phenomenon, which can be used in the next step in order to achieve an accurate and reliable forecast by the EMA strategy. Also, the time series techniques are a suitable tool that can be used to solve the above problem and answer the

question "to what the extent does the EMA measure the desired characteristic?" If we use it in several times in a population, we will not see much difference as a result. The reliability and unreliability of the index trend as a series of data can have a significant effect on its behavior and characteristics, including the EMA. Therefore, we use the ARIMA methodology for this time series.

In Table 2, in order to achieve these goals and in order to ensure the research results and the non-artificial relations in the regression and the significance of the variables, before estimating the model, the reliability test was performed and the unit roots of the research variables in the models were calculated. This was performed using the Eviews11 software and generalized Fisher-Augmented Dickey Fuller (Fisher-ADF) unit root test method as well as Fisher-Phillips-Perron (1999) (Fisher-PP) unit.

Table (2) The results of the reliability test of research variables

Possibility	t-Statistic		
1.0000	**2.415637**	**Generalized Dickey Fuller test statistics**	
	-3.431643	level %1	Critical test values
	-2.861996	level %5	
	-2.567056	level %10	

H0: Existence of single root (variable does not have the required reliability)
H1: No single root (variable has the required reliability)

As the above table shows, the probability value of the generalized Dickey Fuller statistic for each variable of the total index of the Tehran Stock Exchange is more than 0.05. Therefore, it can be said that with 95% confidence level, the null hypothesis that there is a single root is not rejected. In other words, the values of the research variables do not have the required reliability. As a result, the variable "the total index of the Tehran Stock Exchange" is not reliable and is of degree zero, i.e. I(0), so it needs to be differentiated.

Table (3) Generalized Dickey Fuller statistic probability values

Possibility	t-Statistic		
0.0000	**-28.29538**	**Generalized Dickey Fuller test statistics**	
	-3.431643	level %1	Critical test values
	-2.861996	level %5	
	-2.567056	level %10	

H0: Existence of single root (variable does not have the required reliability)
H1: No single root (variable has the required reliability)

As the above table shows, the probability value of the generalized Dickey-Fuller statistic for the total index of the Tehran Stock Exchange is less than 0.05. Therefore, it can be said that with 95% confidence level, the null hypothesis that there is a single root is rejected and the alternative hypothesis, i.e. the lack of a single root, is accepted. In other words, the values of the research variables have the required reliability. As a result, the total index of the Tehran Stock Exchange is reliable of degree one, i.e. I(1), and does not need to be re-differentiated.

In the present study, the Box-Jenkins approach has been used to fit the forecasting model. Using this method, first by entering different autoregressive (AR) and appropriate moving average as well as the OLS estimation, the appropriate model is selected based on the Akaike and Schwarz information criteria and according to items such as the Durbin-Watson statistic, the standard deviation of the errors, R^2 and adjusted R^2, and is shown in Table 4.

The estimates showed that this model was the most suitable in terms of the above criteria. This model had the highest R^2. Also, the information criteria of the Akaike and Schwarz information criteria and the standard deviation of the errors of this relationship were smaller than those of the rest of the relationships. After estimating the model, the smaller inverse of the roots of the AR and MR sentences ensures the reliability of the estimated model. To determine the number of interrupts in this model, the interrupts that were more than once were tested, but it was observed

that one interrupt indicates a more efficient model than the higher number of interrupts does. The number of interruptions in this model was determined based on the above criteria (Schwarz, Akaike, Durbin-Watson, R^2, etc.). Another way to determine the number of interruptions is to pay attention to the Ljung-Box Q (LBQ) statistic at a significance level of 5%. In order to view this, a correlogram can be used. The Q statistic shown in this table confirms this.
Considering the significance of the mentioned coefficients and important cases, the specified model can be considered as follows:

$$R_t = \beta_0 + \beta_1 R_{t-1} + \beta_2 \varepsilon_{t-1} \qquad (4.6)$$

In Table 4, you can see the output of the Eviews software in which the coefficients of the Box-Jenkins forecast model along with the criteria involved in investigating the significance of this relationship. In this table, the number of selected interruptions was assumed to be 4 interrupts. Table 4 also shows the coefficients related to the Box-Jenkins forecast model along with its significance. The number of interrupts of this model was assumed to be 2.

Estimations completed. Chosen AR: 4 Chosen MA: 4
Chosen Differencing: 2

Although the model was considered desirable, but since the variables used in estimating the model (the index trend) were unreliable in the first stage, there was a fear of structural break in the model. The reason is that the relationship between the trend and the EMA in the case of existence of structural breaks can change, while there may be no logical relationship between the independent variables (total index trend) and the dependent variables (EMA), and also the coefficient of determination obtained can be artificially very high and lead to misleading. Therefore, paying attention to the existence of structural break in experimental studies is important and necessary, and not paying attention to it may lead to misleading and unrealistic results (Tayebi et al., 2015).

Table (4) Results of model fitting using exponential moving average

Possibility	t-Statistic	standard error	Coefficients	Variable
0.7873	0.269898	9.85E-07	2.66E-07	C
0.0002	-3.715655	0.067243	-0.249850	AR(1)
0.0000	20.14644	0.040806	0.822091	AR(2)
0.0000	12.96631	0.039155	0.507690	AR(3)
0.0000	-9.840794	0.017776	-0.174925	AR(4)
0.0000	-5.978818	0.066370	-0.396812	MA(1)
0.0000	-16.38324	0.077220	-1.265115	MA(2)
0.8808	-0.149989	0.044235	-0.006635	MA(3)
0.0000	15.41557	0.043416	0.669285	MA(4)
0.0000	107.7470	4.25E-07	4.58E-05	SIGMASQ
-7.148785	Akaike info criterion		0.337060	R-squared
-7.134344	Schwarz criterion		0.335710	Adjusted R-squared
-7.143692	Hannan-Quinn criter.		249.6400	F-statistic
2.001832	Durbin-Watson stat		0.000000	Prob(F-statistic)

As it was seen, with the Dickey-Fuller test, we came to the conclusion that the time series is an unreliable index and it was guessed that there was structural break in it. The existence of structural break in the economic time series can be very common due to shocks such as sanctions and fluctuations of the exogenous variables of the model. Structural break causes the regression results to be inadequate and miss

the ability to predict accurately. Therefore, first, the presence or absence of structural break in the time series has been investigated using the structural break test (Tayebi et al., 2015).

As mentioned above, structural break causes the results of the regression model of the research to not have the necessary validity and miss the ability to predict correctly. Failure to pay attention to it may lead to unreliable and misleading results in relation to the dependent variable (the EMA). Therefore, it is necessary to analyze it due to the necessity to use the trend of the total index in analyses and market timing by the EMA method. There are many ways to solve this problem and considering that existence of structural break in the price index of the Tehran Stock Exchange is likely, we determine break points or severe shocks at different intervals using the net multiple average break test presented by Bai and Perron (2003 and 2019).

5. Analysis of Tests and Research Results

5.1. Determining Break Points Using Bai-Perron Test

According to Bai and Perron's (2003 and 2019) studies, the m-break model (for the mode m+1 regime) is defined as $yt = \beta j + \varepsilon t$ (Kellard and Sarantis, 2008, p. 719). In this relation, βj $(j = 1, \dots, m+1)$ is the average level of yt in the j regime. In addition, for each M-partition $(T1, T2, \dots\dots, Tn)$, the break points correspond to different regimes and $T0 = 0$ and $T_m+1=T$ are assumed. Estimation of the break points will be based on the following objective function:

$$(T1, \dots . Tm) = argmin_{T1,\dots Tm} St(T1,\dots,Tm)$$

For each M-partition, the estimates $(T1, \dots . Tm)$ are obtained using the concept of ordinary least squares and by minimizing the following expression:

$$St(T1, \dots . Tm) = \sum_{i=1}^{m+1} \sum_{t+Ti-1+1}^{Ti} (yt - \beta j)$$

By estimating the break points, the corresponding $\beta j(T1, \dots . . Tm))$ is obtained corresponding to each regime. Bai and Perron proposed a dynamic programming algorithm for estimating the above relationship. The selection of final break points is also based on the use of a sequential procedure.

The Bai-Perron multiple structural break point test was performed to determine the endogenous break points between the years from March 20, 2003 to March 19, 2020 for the total index of the Tehran Stock Exchange. The results are shown in the following table.

Table(5) Results of Structural Bipron Failure Test for Total Index Variable

Critical value	Scale	Statistics F	Failure test
**Value	Statistics F		
8.58	18824	18824	0 vs. 1 *
10.13	2463.9	2463.91	1 vs. 2 *
11.14	4380.9	4380.87	2 vs. 3 *
11.83	14.562	14.5625	3 vs. 4 *
12.25	0	0	4 vs. 5
.* Significance at 95% confidence level			
.** Critical Value of Bipron Value, 2003			

As it can be seen, the Bai-Perron test with trimming 0.15 and maximum number of break points 5 was performed at the significance error level 0.05. The results of the structural break point test indicate the existence of 4 structural break points and severe shocks in the time series.

During the study period, the trend of the index changed 4 times and had severe shocks. To determine

the exact date of these breaks, the Hodrick Prescott filter test was used.

5.2. Hodrick Prescott Filter Test

One of the most important topics in analysis of business cycles is the separation of trends and cycles in time series. Although this analysis can be assumed to be a statistical problem, most economists believe in the evolution of economic growth along a given path after short-term fluctuations, so that this path can be considered as a "trend". But economics is affected by two types of shocks, some of which have permanent effects and some of which have temporary effects. Basically, the trend is seen as the part of the evolution of economic growth that is caused by constant shocks, and such a series should be non-stationary in terms of the structure. In contrast, the part of the economy that results from temporary shocks is related to the economic "cycle". In terms of structure, this component must be stationary (Bani Asad and Mohseni, 2014).

According to Blanchard and Fisher's (1995) ideas, there are two types of analysis. The first approach assumes that the trend component of the index is smooth, and therefore most short-term fluctuations are due to transient shocks. The second approach assumes that fluctuations are solely due to permanent shocks and the index and the trend are the same. Technically, the Hodrick Prescott Filter is a double-sided linear filter that obtains a smooth path with the name (τ_t) by minimizing the variance of the y_t series around τ_t with respect to the sum of the squares of two differences of (τ_t).

The Hodrick Prescott filter provides an invisible time trend for the time series variable. The filter was first introduced for business cycle analysis in 1980, but was released in 1997 after a 17-year delay. This method is a single equation method and is more popular than other filtering methods such as the Baxter-King filter. HP filter is a simple statistical smoothing technique and is one of the most common methods used to estimate production efficiency, which can be used for investigating the total index of the Tehran Stock Exchange as well. This filter, as a high-pass filter, minimizes the difference between the actual and potential returns when applying changes to the return of the index for the total sample of observations (T).

Assume that a visible time series (y_t) indicates the real production. The Hodrick Prescott filter decomposes Prescott (y_t) into a time trend (τ_t) and a time series of stationary cyclic elements, such that

$$y_{t=}\tau_t + c_t$$

Note that both τ_t and c_t are invisible, and since c_t is a stationary process, it can be assumed that y_t is the sum of τ_t with a series of perturbations such as ct.
Hence the main problem is extracting τ_t from y_t.
The problem description with the Hodrick Prescott filter design is:

$$\min \sum_{t=1}^{T}(y_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1}[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2$$

The strength of this filter is its flexibility and its weakness is the sensitivity of the results to the coefficient λ.

In this study, y_t is the actual value of the variable (the total index of the Tehran Stock Exchange) in year t; τ_t is the potential value of the variable (the total index of the Tehran Stock Exchange); T is the number of observations; and λ is a boosting factor (balancing value), which determines the smoothing value of the trend so that a small value of it will produce potential returns that are very close to the actual returns.

The answer to the above problem will be a function of parameter λ. The larger this parameter is selected, the smoother the growth series will be and the more the series will move towards linearity so that limit values of zero and infinity can explain how to select it. The Hodrick Prescott filter solves this problem by assigning appropriate weights to signal against a linear trend. Let λ denote weight. If $\lambda = 0$, then $c_t = 0$, and then the answer to the optimization problem is $y_t = \tau_t$ and the series itself. If we assume

that λ is so large such that $\lambda \to \infty$, in this case τ_t approaches the least squares method estimate and Δy_t will be equal to a fixed number. This means extracting a linear time trend as part of the trend. Generally, as this parameter increases, the trend series becomes smoother; and as it decreases, the trend series becomes more volatile.

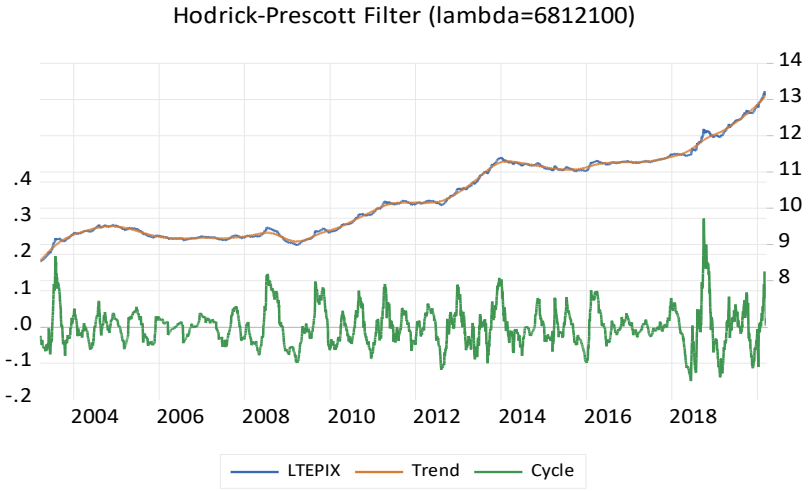

Diagram 3. Hodrick Prescott filter for the total index of the Tehran Stock Exchange.

As can be seen, in the above diagram, the variable "total index of the Tehran Stock Exchange" has been de-trended and the total index of the Tehran Stock Exchange is actually shown along with its two separate components, i.e. the trend component and the cycle component.

Just as all methods of de-trending, the Hodrick Prescott filter has been used to create a new time series of the Tehran Stock Exchange index potentially and to determine its exogenous gap in macroeconomic modeling; and the break points become visible considering the difference between the total index of the Tehran Stock Exchange and the trend.

- The first regime started in 2003 and continued until mid-2009, which was the longest regime in the period under study.

  From the beginning of 2003, the price index of the Tehran Stock Exchange began to accelerate rapidly and had a strong growth until mid-2004, which caused a price bubble in the Tehran Stock Exchange. After that, with the breaking of the price bubble, the downward trend of the Tehran Stock Exchange began and the price index decreased until 2006. Then, the stock index had a period of stability until early 2008. In 2008, at first, the stock price index was associated with a sudden increase, and then with the onset of the global financial crisis from the middle of this year decreased rapidly until the end of 2008. From the beginning of 2009, this index again took a rapid upward trend (Heidari and Bashiri, 2012).
- The next regime was from January 1, 2010 to December 2012.

  The 2007-2008 US financial crisis is one of the biggest economic crises in the United States since the 1930s. Some have likened this crisis to a massive tsunami that began in the United States and has spread to European countries and then to other parts of the world. Iran was undoubtedly exposed to the damages of this tsunami. Although due to the lack of connection between the Iranian financial market and its low integration with the

global market, the direct and immediate effects of this crisis in the monetary and financial sector were not significant, as in Europe and East Asia, but the indirect and long-term effects of this crisis in the financial markets as well as in the real sector of the economy emerged little by little over years. Also, from the beginning of 2009, this index again took a rapid upward trend and reached from 8,000 units to more than 18,000 units in the middle of 2010. After the global crisis subsided, the Tehran Stock Exchange index had a good upward growth from 2009 to 2011, so that in the two-year period from May 2009 to May 2011 it ascend from 8500 to 26000 units, indicating about 205% net growth. The main reason for this growth can be attributed to the diminishing impact of the global crisis of 2007 and 2008 (A crisis that seems to have just hit the capital market in the current situation) (Heidari and Bashiri, 2012).

- The next period was from January 1, 2013 to the middle of 2018.

The most unprecedented fall of the stock index in the 47-year history of this market before March 14, 2015, which was recorded with a sharp drop of 2388 units of the capital market thermometer on Sunday, January 12, 2014, caused the market to return to the range of 85,000 units, which became known as "Black Sunday". There were various conjectures about the causes of the negative reaction of the capital market; reasons such as the government's decision to curb liquidity, increase bank interest rates, increase feed-in rates for petrochemical units, and the president's order to fight economic corruption were among the most important of these conjectures. After the Black Sunday, the total index of the Tehran Stock Exchange took a downward trend and finally fell to 70,000 units. While the total index experienced a fall about 10%, shareholders in many symbols experienced a fall about 50%. After a sudden fall, the Tehran Stock Exchange index had continued its slow and downward trend until the early winter of 2015, so that until then, the stock market index remained at 62,000 units (World Economy, December 17, 2013).

- The third regime started in the middle of 2018 and continued until 2020.

The Iranian economy began the year 1997 with a sharp acceleration of currency prices to set new records. According to reports on Eqtesadnews, a study on the factors affecting the markets shows that incorrect monetary, currency and trade policies, the US withdrawal from the Joint Comprehensive Plan of Action and the return of sanctions along with trade war among the world's biggest economies has had the greatest impact on the sharp jumps and falls of the Tehran Stock Exchange index during 2018. At the same time, the intensification of environmental risks, especially in the second half of the year, has led to behavioral deviations and a temporary change in stock traders' tastes. One of the events affecting the stock market in 2018 was the one-sided withdrawal of the United States from the Joint Comprehensive Plan of Action and the beginning of the US sanctions and pressure in the first half of 2018, which caused sharp fluctuations in the currency and inflation rates (macroeconomic factors). These risks, which were beyond the influential capacity and individual control led to structural breaks in the second half of 2018 so that 2018 witnessed the sharpest growth and the most significant daily declines. According to the statistics in the empirical background of the research, half of the strongest growths and half of the most drastic daily declines of the total index of the stock during the study period occurred in 2018, and at the same time with the arrival of large amounts of liquidity, the record of volume and value of retail transactions was also broken (Donyae Eghtesad newspaper, No. 5120, March 1, 2017).

Different stock exchanges around the world have now experienced different financial crises, and subsequently, occurrence dates of these crises have been determined by experts. No matter what are the

types and the occurrence causes of the financial crises, in comparison with the Rahimi Baghi's et al. (2018) study, the stock exchange has suffered from financial crises during the period from September 21, 2004 to March 11, 2009. In this study, investigating the trend of the total index of the stock exchange and analyzing the results of the Bai-Perron test, their findings were confirmed and in addition, it was found that the index has changed fundamentally in four stages from the beginning of 2003 to the end of 2019. If our time series has many break points, using this method is practically very difficult and will not work.

In addition to using regression estimation of multiple time series, single time series can also be used to determine the break points. Given that the aim of this study was to investigate significant breaks in single time series of price, a pattern with an average value (the intercept component as an independent variable) or an autoregressive (AR) pattern can be estimated and then it can be determined if there is a significant break(s) in this process. According to the results obtained from the correlogram, the first and second interrupts for the moving average, auto-regression, and partial auto-regression are out of lines and also the probability value (Prob) is less than 0.05; thus the null hypothesis that there is not self-covariance or autocorrelation between the data is rejected, indicating that the choice of the first and second interrupts for the moving average and the auto-regression component is significant, or that there is autocorrelation or AR between the data.

Structural break causes the results of the regression model (the Autoregressive Moving Average (ARMA) model) of the research to not have the necessary validity and miss the ability to predict correctly. . Failure to pay attention to it may lead to unreliable and misleading results in relation to the dependent variable (the EMA). Therefore, it is necessary to analyze it due to the necessity to use the trend of the total index in analyses and market timing by the EMA method. Therefore, then we will perform the clustering test and investigate the effect of the K-Means clustering on the validity and resilience of the EMA as a tool for timing. Therefore, the total index should be divided into categories and each individual category should be smoothed. With smoothing we mean to eliminate the effects of outlier data on the diagram, and then in each category the exponential moving average is recalculated and validated. For this end, we cluster the data of the total index.

K-Means Clustering Test

Clustering divides an irregular population into a set of regular subgroups. In clustering, the objects are grouped according to the principle of the highest similarity between the members of each cluster and the lowest similarity between different clusters; i.e. the clusters are arranged so that the objects are most similar to each other within each cluster and most different in the data of other clusters. When all the characteristics are continuous, the similarity criterion is usually expressed by the Euclidean distance, and otherwise, a suitable criterion is considered for it (Gharib et al., 2019). The partitioning and hierarchical clustering methods are among the main clustering methods.

Partitioning clustering: Suppose we have a database containing n objects. A partitioning method creates K partitions from these data in such a way that each partition represents a cluster; in other words, the data are clustered into groups so that each group must have at least one object and each object must belong to only one group. Of course, the second condition in the fuzzy partitioning methods can be flexible. The K-means algorithm was one of the first partitioning clustering algorithms being used extensively and effectively in real data applications in data set clustering. This method is one of the centrifugal partitioning clustering methods that was first introduced by McQueen. In this method, it is assumed that the clusters are convex and the center of the cluster is a good representative of that cluster. This method is designed for clustering quantitative data. After classifying the index into 4 clusters, which is same as the number of structural breaks during the trend, in the next step, the distance of each option from the average of each cluster is calculated. If the distance of the option considered is far from the average of its

cluster and is closer to another cluster, this option is assigned to the closer cluster. This process is repeated until the error function is minimized or the members of the clusters do not change (Yuti and Sharma, 2013).

$$EF = \sum_{i=1}^{K} \sum_{x \in ci} d(x, \mu(ci))$$

Algorithm is one of the common and efficient methods in clustering that considers "the number of clusters" as input and partitions the set of objects into clusters. This algorithm works as follows:

1) Randomly selects the objects as the centers of the initial clusters;
2) Assigns each object to the clusters considering its most similarity to the centers of the clusters;
3) Updates the centers of the clusters; i.e. it calculates the mean value of the objects in each cluster;
4) Refers to the second stage until there is no change in the clusters (Tan, Steinbach and Kumar, 2006).

In this relation, μ represents the center (mean) of the cluster and d (x, μ(ci)) denotes the distance of each option from its center. Suppose that we must divide the observations (x1, x2,… , xn) with a dimension d into k parts or clusters. We identify these parts or clusters by a set called S which is defined as S = {S1, S2,… , Sk}. The members of the clusters must be selected from the observations in such a way that the function "Within Cluster Sum of Squares (WCSS)", which is similar to variance in one-dimensional mode, is minimized.

$$\text{Arg}_S \min \sum_{i=1}^{k} \sum_{x \in si} \|x - \mu i\|^2 = argsmin \sum_{i=1}^{k} |si| varsi$$

Here μi refers to the mean of cluster Si and | Si | is the number of members of the i^{th} clusters. Of course, it can be shown that the minimizing this value means maximizing the mean of "Between-Cluster Sum of Squares (BCSS)" because according to the total variance law, as the value of the WCSS decreases, the value of the BCSS increase due to the fixed total variance.

The results of the clustering test by the Eveiws software are presented in the following tables.

Table(6)Clusters and values of the centers of each cluster

Cluster				
4	**3**	**2**	**1**	
11.23	12.38	10.16	9.25	Logarithm of the total index

Table(7)Number of data per cluster

Weight given to each cluster	number	Cluster	End date	start date	The logarithmic mean of the total index
10%	1923	1	1389/05/13	1382/01/04	9.25
20%	724	2	1392/03/06	1389/05/14	10.16
30%	413	3	1397/05/25	1392/05/07	12.38
40%	1373	4	1398/12/28	1397/05/26	11.23
100%	4433	کل			43.02

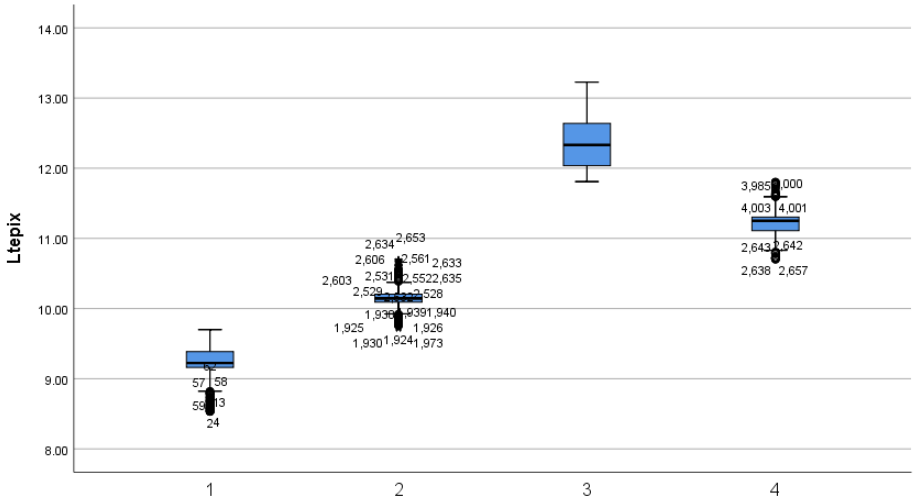

Figure 4 - Data distribution in each cluster

Fitting the Model after Clustering

In order to be able to use our regression model for timing and forecasting by the EMA method, the K-Means clustering has been used. Due to the fact that in the Bai-Perron structural break point test, four break points were detected in the period under study, the data were divided into four clusters or classes using the K-Mean clustering method. Then the convex combination method was used to construct a composite index and to combine the data and each cluster was weighed into the data with respect to the time sequence based on the proximity to today's date, i.e. when performing the clustering.

Table (13) Results of model fitting using moving average

Possibility	t-Statistic	standard error	Coefficients	Variable
0.0005	-3.499488	2.47E-07	-8.64E-07	C
0.0104	-2.569138	0.107996	-0.277458	AR(1)
0.3854	-0.868574	0.394004	-0.342221	MA(1)
0.1824	-1.334456	0.269677	-0.359872	MA(2)
0.0765	-1.773665	0.047734	-0.084664	MA(3)
0.7645	-0.299632	0.711677	-0.213241	MA(4)
0.1639	1.393496	2.14E-07	2.98E-07	SIGMASQ
-12.16178	Akaike info criterion		0.312637	R-squared
-12.11979	Schwarz criterion		0.307274	Adjusted R-squared
-12.14563	Hannan-Quinn criter.		58.29463	F-statistic
1.980483	Durbin-Watson stat		0.000000	Prob(F-statistic)

Estimations completed. Chosen AR: 1 Chosen MA: 4
Chosen Differencing: 2

In the risk-measuring model of the fluctuation index, the convex moving average was estimated based on the EMA method.

As the above table shows, a significance level for the AR and MA values that are less than 0.05 indicates that the first-order autoregression and the first-order moving average for the total logarithm index of the Tehran Stock Exchange as well as for the convex index are significant. The Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC), and the Hannan Quinn Criterion (HQC) of the estimated equations were used as the basis for selecting the optimal interrupt of the patterns. As in can be seen in the above tables, the values of these three criteria were smaller for the convex moving average, so this model (the convex moving average) performs better than the simple exponential moving average do for determining signals.

6. Results

The empirical literature shows that the benefits of avoiding structural economic shocks often outweigh the benefits of involving in an upward market, and market timing strategies, which include frequent shifts based on short-time forecasts, as a tool to achieve this goal need high forecast accuracy to justify their trading costs. Motivated by this argument, this study seeks to develop conservation-based moving average timing strategies aiming at maintaining stock portfolio values over long time periods and against uncertainty in order to reduce unfavorable effects of systemic risk. As seen in the experimental literature, the signals generated by the EMA model lag behind real economic events, resulting in ineffective strategies for long-term recessions. Therefore, in this research, in the first stage, using the exponential moving average, the suitable ARIMA model was estimated and different methods were used to determine the coefficients of the model. Then after fitting the model by the Box-Jenkins approach, finally the ARIMA (4,2,4) model was identified as the suitable model and a suitable estimate was made. We also realized the existence of 4 structural breaks in the total index trend using the Bai-Perron test. Then the index was de-trended by the Hodrick-Prescott filter test, and a new index was created for use in the K-Means clustering. Since the existence of structural breaks in the model means that the trend has changed its directions abruptly and these models do not have good results in the case of structural breaks, in order to increase the goodness and fitness of the model, clustering was performed by the K-Means model and 4 clusters with a same trend were formed, which were weighted with respect to their sequence; thus the newer data had higher weights. Finally, after giving weights to the data and determining the number of interrupts of the model, the model was estimated as ARIMA (1,1,4). Then after re-fitting the model by the Box-Jenkins test and comparing the Akaike, Shwarz and Hannan Quinn criteria, it was determined that, in the clustered mode, the goodness and fitness of the model are better than those of the model in the initial state, and the EMA in the clustered mode can show better performance than before. Also, by comparing the MA coefficients in two cases (before and after clustering), it was found that the mean resilience after clustering by the K-Means method is much better than that before clustering. In other words, the sensitivity of this market timing tool in a situation where the market trend is experiencing severe economic fluctuations and shocks, has improved when using the clustering method compared to the sensitivity before clustering, and the moving average in severe economic shocks shows less sensitivity to changes in the independent variable (the index) and its severe shocks; in other words, this tool has been strengthened by the K-Means clustering. Therefore, the results from the predictions obtained from this tool can be closer to the reality. It is suggested that in future research, this tool should be used in a clustered mode to predict and signal the market and its results for timing during severe economic shocks should be tested experimentally.

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Notes

[1] :Binominal test