# CHAOTIC ANALYSIS AND DESIGN OF AN EARLY WARNING SYSTEM FOR INFLATION IN IRAN USING MARKOV SWITCHING AUTOREGRESSIVE APPROACH

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### Abstract

In Iran, one of the most important economic problems in recent decades is the phenomenon of inflation. Achieving a stable inflation rate requires the ability to use efficient and effective tools in economic policy-making. Hence, economic policymakers should have a proper understanding of the effects of the policies applied and be able to adjust their economic instruments with precise inflation forecasts. EWS has been designed and to anticipate inflationary crises and anticipate an impending incident based on signs that appear on the economy before a crisis happens. In this paper, the behavior of inflation rate has been investigated with BDS and maximum Lyapunov exponent tests, with the help of EVIEWS and MATLAB. If the time series of the inflation rate is non-random, a definite nonlinear function can analyze the behavior of the series with the least error. This study was intended to design a comprehensive early warning system for inflation in the country. In this regard, using the inflation rate, the critical points of the Iranian economy between the years 1990 to 2016 were identified and classified. Then, a well-designed Markov switching autoregressive model was used. The results showed that, it takes 1 to 2 periods on average for the high

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inflationary periods and 10 periods on average for the low inflationary periods to change direction.

## Introduction

Inflation is a social and economic phenomenon and should be considered as one of the most complex effects of economics in the present century in the nowadays world. Inflation, as one of the economic phenomena, has always been a concern for government officials and economic experts. Inflation, which is itself caused by various factors, causes many economic, social and cultural consequences such as poverty, disproportionate distribution of income and the spread of financial corruption, which each of these in turn imposes significant costs on the economy (ZaraNezhad et al., 2009). Price stability or low and stable inflation is a global goal shared by monetary authorities around the world. Price stability is important because empirical evidence suggests that inflationary high rates and volatility stimulate consumption, investment, savings and production decisions. These distortions, in turn, lead to inappropriate allocation of resources and ultimately help reduce economic growth. In addition, high inflation will reduce domestic purchasing power and, consequently, affect lower-income families more than other sectors of society. Thus, monetary authorities, by maintaining a low and stable inflation, will contribute to sustainable economic growth.

Various theories and various reasons have been raised to explain the inflation and the cause of the onset or continuation of inflation, which, to some extent, also express different views of economists. The Inflation Monetary Theory, which has been discussed as the Quantity Theory of Money since about two centuries ago, mentions variations in the volume of money as the only cause of inflation. Therefore, if the amount of money in circulation exceeds the amount of production, it will increase the general prices. This theory is presented in two ways: The Fisher Exchange Equation and the Cambridge Equation. In the Fisher exchange, it is pointed out that assuming that the velocity of money circulation and production are constant, prices will increase in the same proportion if the volume of money increases. In the Cambridge Equation, the same assumptions as the Fisher exchange equation are taken into

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account, as each that any change in the volume of money causes a relative change in the general level of prices (Ghafari, 2012).

A new quantity theory of money suggests that inflation is a monetary phenomenon and is referred to as the slogan of Friedman among monetary economists. This means that high and continuous growth of money causes high inflation, and in fact this view is an implicit conception of the quantity theory of money. Beside the quantity theory of money, the oldest and most prevalent theory of inflation is the demand-pull theory of inflation. This theory, which is mostly associated with Keynes name, considers inflation as the result of the surplus of demand for the supply of goods and services provided at current prices under full employment conditions. The cast-push (wage push) theory of inflation, which is another Keynesian inflation theory, mentions a successive increase of production costs due to demand for increased wages as the reason for increased prices and inflation. The cost-push theory of inflation (the push of raw material prices) considers the increase in the price of raw materials due to reduced overall supply as the cause of goods price increases. Structural inflation theory expresses that inflation is due to the status of the structure of the economy, politics, government, culture, and so on, and mentions factors such as the lack of economic infrastructures, the widespread public sector, the existence of prohibitive rules and regulations for private sector manufacturing activities, the growing budget deficit of the government and the disproportionate extent of the service sector as the causes of inflation; and it believes that the way to treatment of inflation is to make changes in the production system, economic structure, and distribution of income.

According to the above-mentioned theories, there are different opinions about the factors causing inflation. In this study, we attempted to investigate these factors in three categories as follows and included representatives of all the economic ideas raised about the source of inflation:

- *The real and public sector of the economy:* According to the demand-pull theory of inflation, the increase in consumption expenditures, investment expenditures, and government expenditures, taking into account the multiplier coefficient of each of them, would increase the demand and consequently inflation. Therefore, the effects of the consumption of the private sector, investment, Growth rate of the stock index, the price of the Iranian gold coin and the debt of the government to the central bank may be referred to as inflation-influencing variables and, on the other hand, as shown in the cast-push

theory of inflation, the labor wage index could affect inflation. Regarding structural inflation, the index of consuming material prices is the representative of this theory. Finally, in this group of variables, we can point out the effects of the budget deficit, government expenditure and the rate of real GDP growth through the production gap.

- *Foreign sector and currency flows:* The effect of the currency exchange rate on inflation has been proven in the research of Cruz (2009), and according to the demand-pull theory of inflation, one can mention the growth rate of export and import of goods and services, and on the other hand, according to the cast-push theory of inflation, global inflation increase and, as a result, an increase in the index of price of imported goods will increase inflation.

- *Monetary and Financial Sector:* Regarding the effect of domestic liquidity on inflation prediction in the studies of Cruz (2009) and Claveria (2003), and on the other hand, monetary theory of inflation, domestic liquidity has been used as an effective variable in inflation. The effect of liquidity growth in demand-pull theory is also expressed as such that the growth of liquidity in circulation at a rate higher than GDP growth creates a new purchasing power that leads to an increase in demand and, if there is no appropriate supply, creates inflation. Also, the rate of bank interest in both monetary theory and cast-push theory is introduced as the leading indicator of impact on inflation.

Central banks, as monetary policy guides, should have a detailed picture of the future behavior of the prices, or, in other words, a proper forecast of inflation rate in order to make proper decisions. The high importance of low-error forecasting of inflation has led to extensive research in the past decades both at home and abroad. On the other hand, uncertainty is a prominent characteristic of most economic variables, including inflation. This uncertainty and successive changes make prediction difficult and sometimes impossible.

Considering the literature on the roots of inflation in various economics schools, this study explores the factors influencing inflation and investigates how external and internal factors affect inflation rates and how inflation shocks are affected by the growth of variables. Therefore, in this research, we first investigate chaotic inflation and then the warning indicators in predicting inflation based on the Markov switching model.

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**Literature Review**

Nasrollahi et al. (2017), in an article titled "Designing an Early Warning System for Foreign Exchange Crises in Iran: A Logistic Approach" investigated the effective factors on the currency crisis using seasonal data of the economy of Iran over the period of 1988-2014 by means of a discrete dependent variable model, and designed an early warning system for currency crises. The results showed that the variables of the ratio of loans to deposits, the ratio of banks' liabilities to the central bank to the monetary base, the inflation rate, and the growth rate of industrial production have the greatest role in the probability of a currency crisis.

Makatjane et al. (2016), in an article entitled "Inflation Warning System", using the Markov Switching and Logistic Regression approach, surveyed the inflation targeting of South African Reserve Bank (SARB) in 2000, the year that the inflation rate has been low and reached from 8.8% to 2.65%. A warning system was designed to predict the upper limit of the inflation rate. The high and low inflation rate periods are identified by the Markov model and then the results of the classification regime and the logistic regression model are evaluated; the results showed that the designed model has the ability to support and help SARB policies and can be effective in predicting inflationary crises. On the other hand, the logistic regression model insists that by only 54% probability South Africa will be exposed to inflation in the period from 2015 to 2020, so the monetary policy committee will face the protective zone from inflationary crises.

Pourkazemi et al. (2015), in a study titled "Determining the Inflation-Influencing Factors and Designing the Severe Inflation Warning System for the Economy of Iran" identified the major variables affecting inflation in Iran from the monthly data of 21 potential variables influencing inflation, from March 1996 to December 2011, by combining algorithms and neural networks; this variables included the quantity of liquidity, government expenditures, labor wage index, bank interest rates, GDP, inflation with time lag, and the global price of crude oil index; and then the severe inflation warning system is designed. This system, or the neural networks base, predicts the likelihood of severe inflation over the next six months, and the results also indicated that the system performance is promising and is able to issue early warning signals for severe inflation occurrence in the future.

Ghasemi et al. (2013), in a study titled "A study of Chaotic Processes and Forecasts of Iran's Exchange Rate in 1980-2012",

discussed the issues related to the chaos theory in the Iranian foreign exchange market during the years 1980-2012. In this study, they examined the behavior of exchange rate using BDS tests and the largest Lyapunov exponent with MATLAB; and then, prediction took place inspired by the ARIMA process. Their results indicated that the time series were non-linear and chaotic.

Zaman (2013) stated that in order to accurately predict the future inflation rate, it is essential to take into account the basic trend of inflation. This is important for the medium- and long-term prediction. In this research, a simple but powerful technique has been used to combine this process into models, and standard statistical time series reports are used for high precision. The results showed that the trend composition estimated by modeling inflation as the deviation from the main trend has led to a high-precision prediction of about 20% to 30% from 2 years to over 3 years.

Cruz et al. (2013), in an article entitled "Inflation Warning System in the Philippines, using Markov Switching and Logistic regression models", designed an early warning system model to predict high inflation in the Philippines. Upper and lower limits of inflation were identified using the Markov model, and then, using the classification regimen results, logistic regression models have been considered with the aim of quantifying the probability of occurrence of the upper limit. The results showed that the suggested EWS model has some of the potential complementary tools in the monetary policy of the Philippines based on direct and indirect sampling in prediction performance. On the other hand, the results indicated that inflation in the Philippines may be modeled by two MS_AR (2) modes. Other results indicated that this country may be more in the lower limit of inflation than the upper limit of inflation and, in general, Markov Switching results supported effective Philippine monetary policy.

Ebrahimi et al. (2012), in a study entitled "Designing an Early Warning System (EWS) for Currency Exchange Crisis in Iran, Using the Markov Switching Approach", designed a comprehensive EWS for monetary crises. In this regard, using the free-market exchange growth rate, they identified and classified the currency exchange crises and examined early warning indicators in three categories of foreign trade and currency flows, the status of the real and macro sector of the economy, as well as the monetary and financial sector. In order to identify and anticipate the crisis, among all affective variables, finally, the GDP growth rate, the ratio of the budget deficit to GDP, the

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logarithm deviation of the effective real exchange rate, the growth of foreign exchange earnings from oil exports, the ratio of change in M2, and the ratio of the current account deficit to GDP has been selected and the result of the model's estimation has shown that the selected crisis cycles in the period of the study have shown the crisis and they are consistent with the realities of the economy of Iran.

Jamshidi (2012) presented a dissertation titled "Reviewing the Currency Exchange Crisis and Effective Factors in Its Forecasting in Iran's Economy". In this dissertation, the Signaling Approach is used to identify the factors affecting the prediction of the occurrence of the currency crisis using seasonal data for the period of 1988-2007 and 1997-2005 in the economy of Iran. Using this approach, the most effective indicators in forecasting crisis were identified respectively as the growth rate of the value added of the industry and mining sector, the rate of GDP growth, the growth rate of government debt to the central bank, and the growth rate of liquidity to foreign reserves. According to the results of this research, the most effective variables affecting crisis prediction, based on the lowest noise to signal ratio, are respectively: the growth rate of value added of the industry and mining sector, the GDP growth rate, the growth rate of government debt to the central bank, the growth rate of liquidity to reserves, and growth rates of foreign reserves.

Sharmishtha (2012), in a paper entitled "Early Warning Forecasting System for High-Inflation: The Neuro-Genetic Network Model for the Indian Economy" studied a synthetic network model based on the logarithm for an early warning system. This early warning system employs some of the economic variables as inputs and estimates an ANN model to quantify the probability of inflation in a fixed period. This algorithm is used to optimize the structure of the ANN model. Empirically, the suggested neuro-genetic pattern was used to identify the category of leading economic indicators; and eventually, a signaling early warning system for the high inflation rate was made using the Indian economy data. In addition, the comparative results for the proposed model are derived from a pattern of signal data.

Molla Bahrami et al. (2011), in a study titled "A Comparison of Inflation Forecasting based on Random Differential Equations with Competing Models", attempted to predict inflation in the Iranian economy. Initially, the time series of inflation was explored in term of the chaotic feature with monthly data and then, based on the random differential equation, a dynamic model for predicting the behavior of the time series of inflation was designed. Based on the RMSE, MAE and

RMS criteria, the random differential equations model has fewer errors in predicting inflation compared to its competing models.

Shajari et al. (2010) presented a probabilistic model for forecasting bank crises and balance of payments in Iran's economy by means of a signaling method and investigated the possibility of overlapping of two crises (Twin Crisis) in a study entitled "Forecasting Bank Crisis and Balance of Payments using the KLR signaling method (Case Study: Iran)". The results of this study showed that the signaling method, despite its nonparametric nature, can provide a warning system for crises. In the monetary crisis, the currency market push index has been used and the results indicated that the stock price index and real interest rate are the most suitable variables in predicting the bank crisis and balance of payments. On the other hand, other suitable indicators for warning include import index and oil prices; while the index of credits for GDP, contrary to the expectations, has not been a good predictor of the bank crisis in Iran.

### Theoretical Principles and Model Specification

#### Chaos tests

In general, two points of view have been proposed for assessing the status of complex time series. The first view examines the question of whether the considered time series was created by a definite or random process. In the second view, it is attempted to determine whether a time series indicates a chaotic or non-chaotic behavior. The methods used in the first approach rely on the analysis of the correlation dimension of the system. The methods in the second view mainly include the analysis of the largest Lyapunov exponent, which will be further explained.

#### Early Warning System

The goal of designing early warning models is to predict crises. It means to be able to identify periods of crisis, the beginning of crises or, if possible, their duration. In order to correctly execute this design, two issues should be considered: the specification of the EWS models and their evaluation.

In the structure of the primary warning system model, two methods are more applicable. These methods include logit-probit and signaling. The multiple logit-probite methods have more application; in fact, this method allows for a more meaningful statistical analysis of the explanatory variables. These types of models need larger samples so that they can estimate only a limited number of explanatory variables without collinearity.

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On the one hand, the signaling method is often applied to single-variable models (which includes a set of leading indicators). Therefore, these selected indicators historically related to the crises have different behaviors in the onset of the crisis up to their threshold. As a result, single-variable models with low samples are more reliable and it is assumed that there are no restrictions on explanatory variables.

The three approaches that are most widely used in the economic literature for designing early warning systems include Limited dependent variable (LDV) approach, signaling approach, Markov-switching approach.

Intrinsic constraints in LDV and signaling approaches have led economists to use the Markov-Switching approach to model turbulence periods. In this approach, the problems of the other two models are avoided by identifying ordinary and turbulent periods in an endogenous manner (Abiad, 1993; and Mariano, Abiad, Gultekin, Shabbir and Tan, 1993). Another advantage of the Markov-Switching approach is that, unlike the other two methods, it uses all the information stored in dynamics. The Markov-Switching model presented by Hamilton (1989 and 1999) is the beginning of the study of exchange rate dynamics using these models, which was one of the areas for studying monetary crises. For example, Engel and Hakkio (1996) examined the currencies in the monetary system of Europe using the Markov-Swinging approach with Time-Varying Transition Probabilities (TVTP) and considered two stable and turbulent regimes in their model. The turbulent period happens during the re-ordering of money in the monetary system band of Europe, which is dependent on the possibility of transferring the position of that currency to the European monetary system. They showed that the probability of re-ordering is dependent on the regime that belongs to that period.

Switching-regime models are a very useful tool for economists, and their application history dates back to many years' ego and studies conducted by Quandt (1958), Goldfeld and Quandt (1973) and Hamilton (1999). These Markov-switching models with Fixed Transition Probabilities (FTP) are used to examine interest rates (Hamilton, 1988), gross national production behavior (Hamilton, 1989), stock returns (Cecchetti, Lam and Mark, 1999), and floating exchange rates (Engel and Hamilton, 1999) (Ebrahimi et al., 2012).

### *Markov Switch*

Invisible variable in this model follows a two-state Markov chain, the first order$\{S_t\}_{t=1}^{T}$, and a chain St=1 indicates the state of the crisis

and St=0 indicates normal status. Although St is not directly observable, the behavior of our dependent variable yt, which can be a change in the nominal exchange rate or the index of the speculative push to the currency market, is dependent on St, such that:

(1) $$\left((y_t|S_t)\right)^{iid} \sim N(\mu_{S_t}, \sigma_{S_t}^2)$$

So both the mean and the variance of yt can change with regime change.

The density of yt conditional on St is as follows:

(2) $$f(y_t|S_t) \frac{1}{\sqrt{2\pi\sigma}} exp\left(\frac{-(y_t - \mu_{S_t})}{\sigma_{S_t}^2}\right) \quad S_t = 0,1$$

The invisible variable of the switching regime varies according to the transition probability matrix under Pt:

(3) 
$$
\begin{bmatrix}
\begin{array}{l}
p_{00}^t \\
\Pr(S_t = 0|S_{t-1} = 0, x_{t-1}) \\
= F(x_{t-1}\beta_0)
\end{array} & \vdots &
\begin{array}{l}
p_{01}^t = (1 - p_{00}^t) \\
\Pr(S_t = 1|S_{t-1} = 0, x_{t-1}) \\
= 1 - F(x_{t-1}\beta_0)
\end{array} \\
\cdots & \vdots & \cdots \\
\begin{array}{l}
p_{10}^t = (1 - p_{11}^t) \\
\Pr(S_t = 0|S_{t-1} = 1, x_{t-1}) \\
= 1 - F(x_{t-1}\beta1)
\end{array} & \vdots &
\begin{array}{l}
p_{11}^t \\
\Pr(S_t = 1|S_{t-1} = 1, x_{t-1}) \\
= F(x_{t-1}\beta_1)
\end{array}
\end{bmatrix}
$$

Where $P_{ij}^t$ is the probability of moving from the state i in the period t-1 to the state j in period t. F is a cumulative distribution function, usually a normal c.d.f or logistic.

The vector elements of xt-1 which are k×1, are early warning indicators that can affect the transition probabilities.

The last element completing the model is the initial value $p_1^1 = \Pr(S_1 = 1)$, which gives us the unconditional possibility of status 1 at a time. Dybeld, Vinich and Lee (1994) argue that the attitude to this amount depends on whether xt is mana. If xt is mana, $p_1^1$ is simply a long-term probability of S1 = 1, which in turn is a function of (β0, β1). If xt is not mana, then $p_1^1$ is another parameter to be estimated. In practice, if the time series is long enough, the value of $p_1^1$ has a negligible effect on the likelihood function and it will not make a difference if it is computed as a function of (β0, β1), estimated as a separate parameter or is only considered equal to a fixed value.

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The estimation process used in this study is the straightforward maximization of the likelihood, which is calculated using the replication described in Hamilton (1994, pp. 692-693). Using the available information up to time t, $\Pr(S_t = j\Omega_t; \theta)$ can be constructed. The conditional (filtered) probability is that tth observation is generated by the j regime and j = 1,2, ..., N, where N is the number of states. In this article, N=2. These conditional probabilities are summed together in a vector N × 1 called $\xi_{t|t}$.

Using conditional probability (prediction) of being in the regime j at time t+1, according to the information available up to time t, it is possible to form predictions $\Pr(S_t = j\Omega_t; \theta)$ for j = 1,2, ..., N. Combine these prediction probabilities in a vector N × 1 called $\xi_{t+1|t}$. Finally, assume that the ηt is a vector of N × 1 whose jth element is the conditional density of yt in equation (2). These predicted and filtered probabilities for any time t are obtained by repeating the following equations:

$$(4) \qquad \xi_{t|t} = \frac{(\xi_{t|t-1} \circ \eta_t)}{1'(\xi_{t|t-1} \circ \eta_t)}$$

$$(5) \qquad \xi_{t+1|t} = P'_{t+1} \cdot \xi_{t|t}$$

which Pt is a transition probability matrix N×N from period t-1 to period t, which is shown in equation (3) and 0 indicates the element to the element multiplication. Equation (4) calculates the probability $\Pr(S_t = j\Omega_t; \theta)$ as the ratio of joint distribution $f(y_t, S_t = j\Omega_t; \theta)$ to the marginal distribution $f(y_t | j\Omega_t; \theta)$, that the marginal distribution is obtained by some of the joint distribution on the states 1,2, ..., N. Equation (5) implies that as soon as we obtain our best guess about our today's state, for obtaining predictable probabilities of being in different situations in the future period it is enough to multiply it by transpose transition probability matrix P.

Assuming an initial value for the L (θ)'s parameters θ and $\xi_{t|t}$ that in our model are $[1 - P_1^1 \ P_1^1]'$, we can repeat it on (4) and (5), so that $\xi_{t|t}$ and $\xi_{t+1|t}$ are obtained for t=1,2,...,T. The log-likelihood function L(θ) can also be calculated as follows:

$$(6) \qquad L(\theta) = \sum_{t=1}^{T} \log f(y_t | X_t, Y_{t-1}; \theta)$$

which:

$$(7) \qquad f(y_t|X_t, Y_{t-1}; \theta) = 1'\left(\xi_{t|t} \circ \eta_t\right)$$

Therefore, the above expression can be evaluated for different values of θ to obtain the maximum likelihood estimation.

*Characteristics of Dependent Variable*

In determining the dependent variable in the qualitative response model, we can use a "synchronous" approach in which the dependent variable has a value of 1 if the HI is equal to 1 in the mentioned techniques. So if we let H show the high inflation, then we have:

$$(8) \qquad H_t = \begin{cases} 1, if\ HI_t = 1 \\ 0, otherwise \end{cases}$$

In the alternative approach, the simultaneous variable H becomes a default variable. This alternative model predicts whether an inflationary crisis or an event of high inflation will occur over a specified period defined by the researcher.

*Model Estimation*

*Main Variable*

Inflation Rate is the annual rate of the change percent or year-to-year change in the consumer price index (CPI), which is generally the retail price of the ordinary goods that households purchase. CPI is calculated from a base year using the consumption pattern or household basket.

*Statistical and Experimental Results of the Model:*

According to the results of the two filtering approaches, the existence of fluctuating cycles in the country's inflation variable is obvious, so switching may be used after identifying the existence of upper and lower cycles.
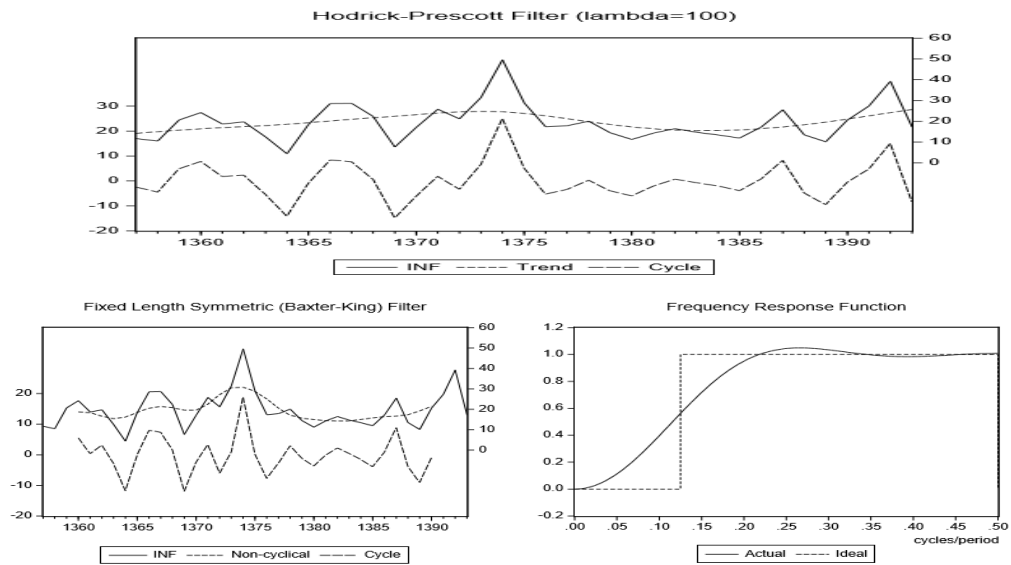
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**Figure 1:** Descriptive Statistics of Inflation Rate

According to Table 1, the normality test statistic states that the inflation rate is statistically normal.

**Table 1:** Inflation Normality Test

| P-Value | JB | Kurtosis | Skewness | Mean | Std Deviation | MIN | MAX |
|---------|-----|----------|----------|-------|---------------|-----|------|
| 0.0002 | 16.63 | 5.1 | 1.21 | 19.59 | 8.85 | 4.3 | 49.9 |

Source: Research calculations

The concept of Lyapunov exponent was used before the emergence of chaos theory to determine the stability of linear or nonlinear systems. The calculation of the Lyapunov exponent is done by measuring the amount of kurtosis or curvature that occurs in a system. In fact, in this method, the average velocity of the two-point transition paths that were initially close to each other and are exponentially diverted is calculated. There are several methods for calculating Lyapunov exponent, including the Jacobian Matrix of the system (Moieni, Abrishami and Ahrari, 2006). A negative Lyapunov exponent means the convergence rate (sustainability) and a positive Lyapunov exponent means the divergence rate (instability). Until the introduction of the chaos theory, the Lyapunov exponent spectrum was used as a measure of the effect of initial conditions on a turbulent dynamic system. The chaos theory, without

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contradicting the definitions, merely states that the positive and negative values of the Lyapunov exponent can coexist in a chaotic natural system. By definition, Lyapunov exponents are independent of the initial conditions and are very useful as invariable properties of the absorbing pathway, so that in examining the predictability of time series of financial markets, the main characteristic of these series, i.e. the chaotic amount of these series, which is based on the Lyapunov coefficients, is considered. This amount determines to what extent the series produced will differ from the main series by changing the initial condition or model parameters (Ghasemi, 2013).

Suppose a time variable model accurately modeled the behavior of a natural system. This definite time variable model may be derived from the differential equation $\dot{x}(t) = X(x(t))$, or in the discrete state it may be the solution of the equation x(t+1)=f(x(t)); it is obvious that knowing the information about the discrete time variable and the initial condition, an infinite prediction is possible. In fact, however, the initial condition is characterized by an inaccurate error Δx(0) and the error value resulting from the initial condition error at time t, i.e. Dx (t), has a behavior as $e^{\lambda t}\Delta x(0)$ function (Δ denotes the initial condition error and D denotes the error of the equation in period t, which is due to the initial condition error), in which, λ is known as the Lyapunov exponent. However, if λ is greater than zero, the system is chaotic and its predictability is limited to time λ-1. By increasing this coefficient, the error in predicting future values increases exponentially. In other words, this coefficient indicates the chaotic amount of a series and high values of it denote high sensitivity of a series to the initial value. Different states may be considered for the lyapunov exponent as follow:

A) the value of λ is smaller than zero, then all the arbitrary initial points converge to a constant point or alternating cycle, so the more negative is the λ, the more stable the system is;

B) The value of λ is equal to zero, then each arbitrary initial point fluctuates around a stable border (limit) cycle, which we call it the stable Lyapunov;

C) The value of λ is greater than zero, then each arbitrary initial point, due to its high sensitivity to the initial condition, rapidly diverge in closed paths, and there are no fixed points or alternating cycles, in this case, the process is chaotic.

High values of this coefficient indicate the high sensitivity of the series to the initial values. If the difference between the initial values is a

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certain amount, then the difference in the series value after a certain
number of the stages is equal to the exponential function of this number.
There are several methods for calculating Lyapunov exponent, including
the Jacobian Matrix system. In this section, we describe how to calculate
the Lyapunov exponent in multi-dimensional spaces. To calculate the
Lyapunov exponent, we use the m-partial vectors of the following
equation:

(9) $$X_i = [x(t_i), x(t_i + 1) \dots x(t_i + m)]$$

From vectors with distances less than r in the following form:

(10) $$r_0(m; i, j) = \left\| X_i^m - X_j^m \right\| \leq r$$
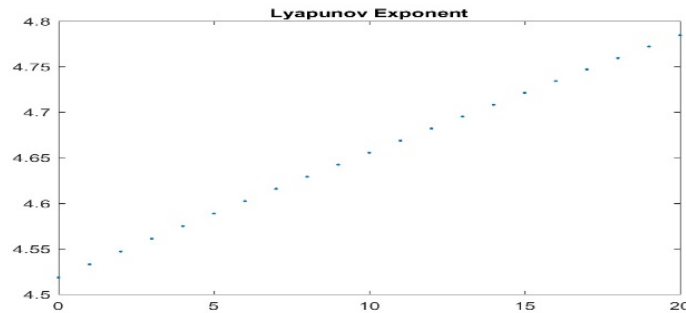
the following expression is computed:

(11) $$d_n(m; i, j) = \frac{\left\| X_{i+n}^m - X_{j+n}^m \right\|}{r_0(m; i, j)}$$

Then the largest Lyapunov exponent is computed as:

(12) $$L_e(m, n) = \sum_{i \neq j} \frac{log[d_n(m; i, j)]}{N(N-1)}$$

The sign Le expresses the nature of the considered time series.
Positive values of Le indicate the chaotic nature of the process and the
difficulty of its predication, and negative values of Le indicate that the
process is non-chaotic and predictable in the long-term.



### Brock Dechert Scheinkman (BDS) Test

This test was developed by Brock et al. (1991) and published by
Brock et al. (1996). This test is a nonparametric method used to test
consecutive correlations and nonlinear structures in a time series based
on the sum of correlation (Behmanesh et al., 2014). The DBS statistic is
derived from studies on chaos theory and nonlinear dynamics, and is not

only suitable for detecting definite chaos but can also be used as a proper diagnostic tool in the goodness of fit test of the estimated model. This test relies on one of the characteristics of the random process compared to the chaotic process. A random process has continuous (infinite) dimension. However, a chaotic process has somewhat limited dimensions; that is, it has a set of points to which the time path is limited to. Therefore, from the calculation of dimensions of a series one can find the process that has created it. According to this method, if the upper series domain was greater than 10, it shows a random process otherwise it would be a chaotic process (Moshiri, 2002). To test the nonlinear effects on the inflation rate, in this study, non-linear methods were used as the BDS; this technique was used in Wang et al. (2005) to test independent processes and nonlinear schemes in time series. This test is as follows:

$$BDS_{m,M}(r) = \sqrt{M}\frac{C_m(r)-C_1^r(r)}{\sigma_{m,M}(r)} \qquad 13$$

In which M has embedded points from space with dimensions m.

**Table 2**: BDS Test Results

| Dimension | Statistic BDS | Std. Error | ZStatistic | Prob |
|---|---|---|---|---|
| 2 | 0.194 | 0.009 | 19.55 | 0.0000 |
| 3 | 0.326 | 0.015 | 20.53 | 0.0000 |
| 4 | 0.417 | 0.019 | 21.84 | 0.0000 |
| 5 | 0.481 | 0.020 | 23.92 | 0.0000 |
| 6 | 0.525 | 0.019 | 26.85 | 0.0000 |
| Raw epsilon | 48.08 | | | |
| Pairs within epsilon | 21836 | V- Statisti | 0.404933 | |
| Triples within epsilon | 306766 | V- Statisti | 0.562690 | |

Source: Research calculations

The results of BDS for the time series of inflation growth with 2 to 6 margin are shown in Table 2. The statistic Z provided in this table is

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used to measure the zero hypothesis of the test. The large values of this statistic or the smallness of the probability test value (zero value) rule out the zero hypothesis based on the independent uniform distribution (randomness) and confirm the other hypothesis, i.e. the general correlation of data (nonlinear random and nonlinear chaotic).

According to the results of the BDS test, the model is estimated and tested for stability of the coefficients by CUSUM, which was discussed in a study by Brown et al. (1975). Fig. 2 shows that the CPI index is unstable because the time series is out of range.
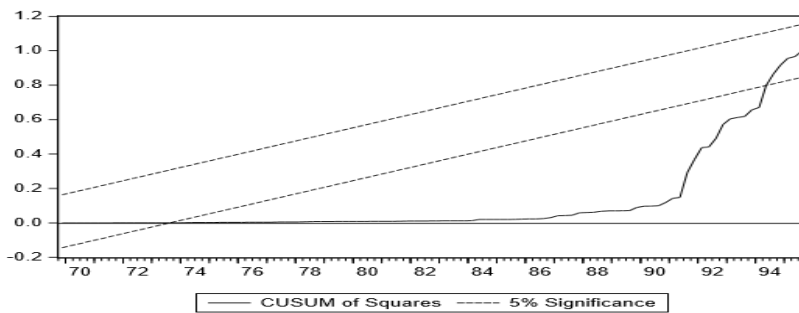


**Figure 2:** CUSUM Test

Following nonlinear tests, the Bai-Peron structural failure test was performed. Out of the results of Table 3, only 5 structural gaps were identified in the period 2Q1995 to 4 Q2013.

**Table 3:** Multiple Breakpoint Test

| Breaks | Number of Coefficients | Sum of squared Residual | Log-likelihood | Schwartz Criterion | LWZ |
|--------|------------------------|-------------------------|----------------|--------------------|-----|
| 0 | 2 | 731.3037 | -252.7711 | 2.019379 | 2.093551 |
| 1 | 5 | 226.6914 | -190. 6955 | 0.980124 | 1.166251 |
| 2 | 8 | 180.1914 | -178.5282 | 0.882538 | 1.181503 |
| 3 | 11 | 168.2399 | -174.8909 | 0.945894 | 1.358635 |
| 4 | 14 | 166.7114 | -174.4072 | 1.068751 | 1.596265 |
| 5 | 17 | 165.9908 | -174.1776 | 1.196404 | 1.839755 |

Source: Research calculations

*The Number of Structural Breaks*

The times in the following table shows the Periods of Structural Breaks. The first failure began in 1995, then it extended to 2005 and finally to 2012.

**Table 4:** Periods of Structural Breaks

| Number of breaks | Break dates | | | | |
|---|---|---|---|---|---|
| 1 | 2012 Q3 | | | | |
| 2 | 2009 Q1 | 2012 Q3 | | | |
| 3 | 2005 Q2 | 2009 Q1 | 2012 Q3 | | |
| 4 | 1995 Q2 | 2005 Q2 | 2009 Q1 | 2012 Q3 | |
| 5 | 1995 Q2 | 1995 Q2 | 2005 Q2 | 2009 Q1 | 2012 Q3 |

Source: Research calculations

**Estimation of Optimal Model Parameters**

The four two-regime Markov switching model is ultimately estimated based on the Akaike criteria, which is better than LR, as Buckly (2004) and Bozdogan (2000) pointed out in their studies. According to the following table, the best model is AR (4) which has a lower Akaike compared with other models. All coefficients of AR(4)-Ms(2) are significant at 5% level.

**Table 5:** Diagnosis of Optimal Model

| Tests | | Models | | | |
|---|---|---|---|---|---|
| | | AR(1) | AR(2) | AR(3) | AR(4) |
| AIC | | 4.6568 | 4.7027 | 4.4436 | 4.5261 |
| Linearity test (Likelihood Ratio) | Coefficient | 23.298 | 18.35 | 36.262 | 22.652 |
| | prob | 0.0000 | 0.0004 | 0.0000 | 0.0000 |
| Normality test (Chi-Square) | Coefficient | 5.6065 | 20.628 | 13.233 | 6.119 |
| | prob | 0.0606 | 0.0000 | 0.0013 | 0.0469 |

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| ARCH 1-1 test (F) | Coefficient | 0.2256 | 1.0987 | 3.1242 | 0.299 |
|---|---|---|---|---|---|
| | prob | 0.6358 | 0.2972 | 0.0803 | 0.5858 |
| Portmanteau test (Chi-Square) | Coefficient | 100.86 | 36.471 | 10.575 | 26.410 |
| | prob | 0.0000 | 0.0003 | 0.5656 | 0.0094 |

Source: Research calculations

Finally, Table 6 shows the estimated AR (4) model in which all of AR (4) parameters are significant at 5% level. The misspecification of the model is then examined by the Ramsey RESET test. The main purpose of this test is to investigate the model variance instability. In this case, the F statistic of the RESET test with a probable value of 0.0017 is significant, so the results are in accordance with the CUSUM and the BDS tests and there are nonlinear cases in the dataset.

**Table 6:** Estimation of Markov Switching Model

| Parameter | Coefficients | Stand Error | ZStatistic | prob |
|---|---|---|---|---|
| C1 | 10.97520 | 1.292853 | 8.489056 | 0.0000 |
| C2 | 4.447593 | 0.438991 | 10.13139 | 0.0000 |
| sigma | 0.686192 | 0.077869 | 8.812156 | 0.0000 |
| RESET TEST | 5.526802 | | | 0.0017 |

Source: Research calculations

The interesting part of this estimation is the probability of transition to regimes. As follows:
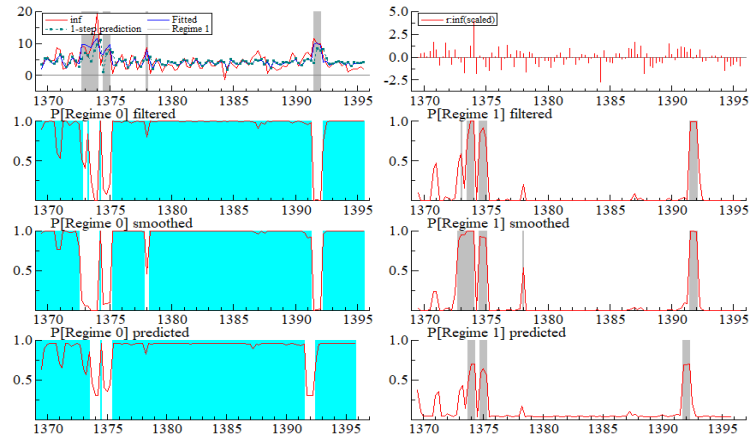
**Table 7:** The Probability of Transition to Regimes

| | Low Inflation | High Inflation |
|---|---|---|
| Low Inflation | 0.585330 | 0.414670 |
| High Inflation | 0.024531 | 0.975469 |

Source: Research calculations

The probability of filtering, smoothing, and predicting probabilities for each regime is shown. It is seen in the figure below that low inflationary periods are low which is consistent with the previous results,

meaning that the time of the low inflation is more than twice the time of high inflation.

**Figure 3:** Chart of Probabilities of High and Low Inflation



The results of the Markov Switching model are also used to show the high and low inflation periods. Using the OxMetrics, the high and low inflation periods are shown in Table 8.

**Table 8:** Episodes of High and Low Inflation

| High Inflation | Low Inflation |
|---|---|
| 1996 Q1 – 1993 Q3 | 1993 Q2 – 1992 Q4 |
| 2007 Q4 – 2009 Q4 | 1996 Q3 – 1998 Q4 |
| 2013 Q4 – 2014 Q4 | 1999 Q3 – 2007 Q3 |

Source: Research calculations

**Conclusion and Recommendations**

In this study, maximum Lyapunov exponent and BDS tests were used to investigate the chaotic nature of the time series of inflation rates. The BDS test was used to investigate non-randomness and confirmed the results of chaos existence in the data generator system. The Lyapunov exponent test was used directly to investigate the chaos. According to the results, Lyapunov exponents are positive in all dimensions and therefor the time series of inflation rates are chaotic. Considering the most important characteristic of the chaotic system, i.e. sensitivity to the initial conditions, it is recommended that there should not be extreme control over the inflation rate since doing so may lead to the butterfly effect.

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Using the results of the nonlinear and chaotic process, the inflation rate was shown and then, by specifying an autoregressive model in the inflation data, the switching regime in Iran's inflation rate was investigated. The results showed that Markov switching autoregressive model has been able to identify the shocks to Iran's inflation rate and the origin of fluctuations and divide the inflation rate into two upper and lower fluctuation regimes. In Iran, stability in the high inflation regime is less than the low inflation regime. Given the autoregressive process of inflation, it could be claimed that the role of anticipation is also determinative in inflation in Iran.

**REFERENCES**

Abiad, M. (2003). Early Warning Systems: A Survey and a Regime-Switching Approach (EPub). International Monetary Fund.

Abounoori, E., & Erfani, A. (2006). Prediction of The Probability of Currency Crisis Within OPEC Countries. Tahghighate Eghtesadi, Issue 73 (In Persian).

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of applied econometrics,18, 1-22.

Bozdogan, H. (2000). Akaike's information criterion and recent developments in information complexity. Journal of mathematical psychology, 44, 62-91.

Bussiere, M., & Fratzscher, M. (2006). Towards a New Early Warning System of Financial Crises. Journal of International Money and Finance, 25(6), 953–973.

Chui, M. (2002). Leading Indicators of Balance-of-Payments Crises: A Partial Review. Bank of England Working Paper 171, London.

Cruz, C., & Dacio , J. (2013). Tenets of Effective Monetary Policy in the Philippines. forthcoming, BS Review.

Demirgüç-Kunt, A., & Detragiache, E. (1998). The determinants of banking crises in developing and developed countries. Staff Papers-International Monetary Fund, 81-109.

Ebrahimi, I., & Tavakolian, H. (2012). An Early Warning System for Exchange Rate Shock in Iran by Markov switching Model. The 22nd Annual Conference on Monetary and Exchange Rate Policies, (In Persian).

Esquivel, G., & Larrain, F. (2000). Explaining Currency Crises. El Trimestre Economico 67, 191–237.

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning. Springer.

Kaminsky, G., Lizondo, S., & Reinhart, C. (1998). Leading indicators of currency crises. Staff PapersInternational Monetary Fund, 1-48.

Kibritcioglu, A. (2004). An Analysis of Early Warning Signals of Curency Crisis in Turkey 1986-2204. From www. Kibritcioglu.com.

Mariano, R., Abiad, A., Gultekin, B., & Shabbir. (2002). Markov Chains in Predictive Models of Currency Crises-With Applications to Southeast Asia.

Naderi, M. (2004). An Early Warning System for Detection of Financial Crises in the Economy of Iran. Iranian Journal of Economic Research, Issue 17 (In Persian).

Nasrollahi, M., Yavari, K., Najar Zadeh, R., & Mehregan, N. (2017). The design of an early warning system of currency crisis in Iran: A logistic regression approach. Tahghighate Eghtesadi, Issue 118 (In Persian).

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. Journal of accounting research, 109-131.

Porkazemi, M., Biravand, A., & Delfan, M. (2016). Designing a Warning System for Hyperinflation for Iran's Economy. Journal of Economic Research and Policies, Issue 76 (In Persian).

Sayadnia Tayebi, E., Shajari, H., Samadi, S., & Arshadi, A. (2010). Explaination an Early Warning System for Identification of the Financial Crisis in Iran. Journal of Monetary & Banking Researches, Issue6 (In Persian).

Shajari, P., & Mohebi Khah, B. (2010). Early Warning System for Currency and Banking Crisis in Iran (KLR- Signaling Approach). Journal of Monetary & Banking Researches, Issue4 (In Persian).

Tong, H. (2012). Threshold models in non-linear time series analysis. Springer Science & Business Media, Vol. 21.

WA, B., DA, H., & LeBaron, B. (1991). Nonlinear Dynamics, Chaos and Instability:Statistical Theory and Economic Evidence. The MIT Press, Cambridge MA.

WA, B., Dechert, W., Scheinkman, J., & LeBaron, B. (1996). A test for independence based on the correlation dimension. Econ Rev 15(3), 197-235.

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*www.ijceas.com*

Wang, W., Vrijling, J., HAJM, P., Gelder, V., & Hydrol , J. (2005). Testing for nonlinearity streamflow processes at different timescales. 1-22.

Zarra Nezhad, M., & Shahram, H. (2009). Prediction Of Inflation Rates In IRAN Using Dynamic Artificial Neural Network (Time Series pproach). Quarterly Journal Of Quantative Economics(Quarterly Journal Of Economics Review), 145 to 167 (In Persian).