

Designing an Early Warning System for Currency Crisis in Iran's Economy: An Application of Bayesian Averaging and Markov Regime-Switching with Endogenous Transition Probability

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ABSTRACT

The recurrence of periods of severe economic stress and sharp exchange-rate depreciations in Iran over the 2001–2021 period highlights the need for an analytical tool capable of identifying exchange-rate vulnerabilities at an early stage. The primary objective of this study is to develop an early warning system for forecasting currency crises and estimating the probability of transitions between periods of stability and crisis. The main contribution of the paper lies in integrating two complementary econometric approaches. First, Bayesian Model Averaging (BMA) is employed to address model uncertainty and identify key determinants from a broad set of macroeconomic variables and a Google Trends-based uncertainty index. Second, these variables are incorporated into a Markov-switching framework with endogenous transition probabilities to capture the nonlinear behavior of the foreign exchange market. The Bayesian results indicate that the exchange-rate gap, liquidity growth, external-sector conditions, the budget deficit, and the uncertainty index have the highest posterior probabilities in explaining the Exchange Market Pressure (EMP) index. The findings from the Markov-switching model further confirm the nonlinear dynamics of the foreign exchange market and show that the probability of transitioning from a tranquil regime to a crisis regime is significantly affected by these variables. In-sample and out-of-sample evaluations confirm the model's high accuracy in reproducing EMP dynamics and generating timely warning signals ahead of the currency crises of 2012 and 2018. From a policy perspective, continuous monitoring of these key variables, together with structural reforms in monetary and fiscal policy and effective management of expectations, can significantly reduce the likelihood of the economy entering a currency-crisis regime.¹

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Introduction

Financial crises have long drawn the attention of economists and policymakers due to their wide-ranging macroeconomic and social repercussions. Within the broader spectrum of financial instability, currency crises are among the most disruptive episodes because they transmit rapidly through inflation expectations, external balances, and the domestic financial system. A currency crisis—often associated with speculative pressures—typically manifests as a sudden and sharp depreciation of the domestic currency or as a period of intense strain in foreign exchange markets, usually accompanied by substantial losses in international reserves or sharp increases in interest rates aimed at defending the currency (Krugman, 1979; Obstfeld, 1996; Berg and Pattillo, 1999). These events frequently trigger severe macroeconomic dislocations and impose sizeable welfare costs on society.

A large empirical literature documents that financial crises are commonly associated with sustained output losses, rising unemployment, and heightened macroeconomic volatility (Reinhart and Rogoff, 2009; Boudia et al., 2019). These consequences tend to be magnified in emerging and developing economies, where structural fragilities—such as shallow financial markets, dependence on external financing, and exposure to commodity price fluctuations—enhance the propagation of external shocks (Frankel and Rose, 1996; Kaminsky, Lizondo, and Reinhart, 1998). For oil-exporting economies, volatility in global commodity prices directly affects fiscal revenues and foreign exchange inflows (Korhonen and Mehrotra, 2010). When such economies additionally face external constraints—including international sanctions or financial-transaction restrictions—their foreign exchange markets become substantially more vulnerable to abrupt shifts (Pesaran and Mohaddes, 2020). These structural features indicate that the mechanisms driving currency crises in oil-dependent and sanction-affected economies differ fundamentally from those in typical emerging markets. However, the early-warning literature has only partially explored these institutional and geopolitical dimensions, leaving a notable gap in understanding crisis dynamics in this group of economies.

These vulnerabilities are particularly relevant in the case of Iran. Over the past decades, the Iranian economy has experienced several episodes of severe exchange rate instability driven by the interplay of domestic macroeconomic imbalances, fluctuations in oil revenues, and recurrent external shocks. Exchange rate management has often relied on heavily regulated regimes that temporarily contain market pressures but tend to accumulate distortions over time. Once these pressures unfold, adjustments are typically abrupt and costly. The episodes of 2012 and 2018 illustrate how intensified international sanctions, combined with domestic structural imbalances, can generate sharp currency depreciations, rapidly rising inflation, and significant macroeconomic instability.

Given these substantial macroeconomic and social costs, a broad literature has sought to develop Early Warning Systems (EWS) capable of identifying currency-market vulnerabilities prior to crisis onset. Early studies relied on non-parametric signaling approaches (Kaminsky, Lizondo, and Reinhart, 1998), followed by probabilistic frameworks such as logit and probit models (Berg and Pattillo, 1999; Edison, 2003). Although informative, these models face important methodological challenges.

The first challenge is model uncertainty. In environments involving many plausible predictors, different model specifications may produce contradictory conclusions, resulting in unstable or non-robust early-warning signals. Bayesian Model Averaging (Raftery et al., 1997; Sala-i-Martin et al., 2004) offers a structured framework to address this problem by assessing a large space of

model combinations and weighting them by posterior probabilities. Despite its recognized strengths, the existing literature has rarely employed BMA as a systematic pre-estimation filter for nonlinear crisis-prediction models, leaving a clear methodological gap.

The second major challenge lies in the inherent nonlinearity of currency crises. Exchange markets typically alternate between tranquil periods and high-stress episodes, indicating that the underlying data-generating process is regime-dependent. Markov Regime-Switching models (Hamilton, 1989) are specifically designed to capture such nonlinearities. Models with endogenous transition probabilities (Filardo, 1994) further allow changes in macroeconomic fundamentals to influence the probability of switching between regimes. This makes them especially suitable for economies where shifts in fundamentals—such as oil revenues, sanctions intensity, or external imbalances—drive rapid transitions into crisis states. Yet, most empirical applications continue to assume constant transition probabilities or omit systematic variable selection, which limits their explanatory and predictive power (Abiad, 2003; Caggiano et al., 2014).

Taken together, these observations reveal three explicit research gaps:

1. the literature lacks a documented and theoretically grounded integration of systematic variable-selection methods with nonlinear regime-switching frameworks;
2. the theoretical rationale for combining BMA with Markov models featuring endogenous transition probabilities remains underdeveloped;
3. the crisis dynamics of oil-dependent and sanction-affected economies—particularly Iran—have received insufficient attention in early-warning research.

Motivated by these gaps, the present study proposes a unified early-warning framework tailored to the Iranian economy. The framework integrates two complementary components. First, Bayesian Model Averaging serves as a disciplined mechanism for handling model uncertainty and identifying macroeconomic variables that robustly explain exchange market pressure. Second—and forming the core analytical contribution—these selected variables are incorporated into a Markov Regime-Switching model with endogenous transition probabilities, which allows crisis probabilities to respond dynamically to evolving macroeconomic conditions.

By combining a robust variable-selection layer with a nonlinear regime-switching engine, the proposed framework identifies indicators that consistently signal currency-market stress while modeling the dynamic transition from tranquil to crisis regimes. The main objective of this study is to develop and estimate an early-warning system capable of predicting currency crises in Iran and to determine which macroeconomic variables exert the strongest influence on the evolution of crisis probabilities. The empirical analysis evaluates both in-sample and out-of-sample performance and assesses the timeliness and reliability of generated warning signals.

The remainder of the paper is organized as follows: Section 2 reviews the theoretical and empirical literature. Section 3 outlines the data and methodological framework. Section 4 presents and discusses the empirical results. Section 5 concludes with policy implications and directions for future research.

Theoretical Literature

Currency crises are characterized by sharp depreciation or rapid loss of foreign exchange reserves, often driven by speculative attacks and shifts in market expectations (Frankel & Rose, 1996; Kaminsky et al., 1998). The theoretical literature categorizes these crises into three generations. First-generation models emphasize deteriorating macroeconomic fundamentals, such as fiscal deficits and monetary expansion, which undermine fixed exchange rate regimes (Krugman, 1979; Flood & Garber, 1984). Second-generation models suggest that crises can occur even with stable fundamentals if market expectations and policy trade-offs trigger speculative attacks (Obstfeld, 1994). Finally, third-generation models highlight the role of financial sector vulnerabilities, such as excessive foreign currency borrowing and capital flow reversals, in amplifying market instability (Corsetti et al., 1998; Radelet & Sachs, 1998).

Regarding early warning systems (EWS), the literature has evolved from simple signaling methodologies (Kaminsky et al., 1998) to probabilistic frameworks like logit and probit models (Berg & Pattillo, 1999; Edison, 2003). However, these traditional approaches often rely on linear specifications that fail to capture the inherent nonlinearity and regime-dependent nature of currency markets.

Two major methodological challenges persist in crisis prediction. First is model uncertainty; choosing a limited set of predictors can lead to biased results. Bayesian Model Averaging (BMA) addresses this by weighting multiple model combinations based on their posterior probabilities (Raftery et al., 1997; Sala i Martin et al., 2004), though it is rarely integrated into nonlinear frameworks. Second is nonlinearity. Currency markets frequently undergo abrupt shifts between tranquil and crisis states. Markov Regime Switching (MRS) models effectively capture these dynamics by allowing parameters and transition probabilities to change across regimes (Hamilton, 1989; Filardo, 1994).

These dynamics are particularly acute in oil-dependent and sanction-affected economies like Iran. In such contexts, volatility in commodity prices and external financial constraints can rapidly trigger regime shifts in the exchange market (Korhonen & Mehrotra, 2010; Pesaran & Mohaddes, 2020). While existing studies on Iran have explored exchange rate dynamics and sanctions, most rely on linear models that cannot fully account for endogenous regime transitions.

This study fills three critical gaps: (1) the lack of integration between systematic variable selection (BMA) and nonlinear regime-switching (MRS) frameworks; (2) the underdeveloped theoretical rationale for combining BMA as a pre-filtering layer with endogenous MRS; and (3) the insufficient focus on the unique crisis dynamics of sanction-hit, oil-dependent economies. By combining BMA for robust variable selection with an MRS engine for endogenous transitions, this research provides a unified, nonlinear early warning system tailored to the structural complexities of the Iranian economy.

Research Background

A substantial body of empirical research has examined the determinants of currency crises and the performance of various early-warning models. Comelli (2014), using a comparative analysis of parametric logit models and non-parametric signaling approaches for emerging economies, showed that GDP growth, the ratio of reserves to short-term external debt, international reserves, and the current account balance reduce crisis risk, whereas government instability and domestic M2 expansion increase the likelihood of a crisis. Sevim et al. (2014), employing decision trees,

artificial neural networks, and logit models, found that the export-to-import ratio, banking-sector credit, inflation, and trade conditions are among the most influential predictors of currency turmoil, with ANN models displaying superior forecasting accuracy. Jdaitawi (2014), in a study of Jordan, demonstrated that declines in international reserves, deterioration in the trade balance, and rapid monetary expansion strongly raise the probability of a currency crisis. Feldkircher et al. (2014), analyzing data for 149 countries during the global financial crisis, showed that high pre-crisis inflation amplifies exchange-rate pressures, while international reserves significantly dampen exchange-rate volatility. Boonman (2019), using a panel of 35 emerging economies, highlighted that combining multiple pressure indicators yields more reliable crisis classifications than single-indicator measures. More recently, Ferdous et al. (2022), using monthly data for Asian and Latin American emerging economies, provided evidence that weak export growth, a low current-account-to-GDP ratio, subdued GDP growth, strong real exchange-rate appreciation, rapid import growth, and a high short-term-debt-to-reserves ratio serve as robust early signals of currency crises.

In the case of Iran, several empirical studies have focused on identifying key vulnerabilities and developing early-warning tools. Nasrollahi et al. (2017) found that inflation, the loan-to-deposit ratio, GDP growth, and the ratio of banking-sector debt to the central bank play central roles in shaping crisis dynamics in Iran. Bayani and Mohammadi (2019), using a TVP-VAR framework, showed that budget deficits, exchange-rate misalignments, inflation, the export-to-GDP ratio, and liquidity growth are the most important drivers of financial stress. Haji Shahverdi et al. (2019) demonstrated that the exchange rate, banks' liabilities to the central bank, and non-performing loans are crucial determinants of banking distress using an early-warning approach. Salmani et al. (2019), applying logit and Markov-switching methods, showed that the government budget-deficit-to-GDP ratio, the current-account-deficit-to-GDP ratio, and inflation significantly increase the likelihood of a currency crisis. Nasrollahi et al. (2020) documented that inflation intensifies crisis conditions during turbulent periods, whereas real GDP growth is the main factor facilitating post-crisis recovery. Bastanzad and Davoodi (2022), using data-mining techniques and Lasso regression, found that domestic savings deficits and liquidity pressures in the banking system lead to base-money expansion, higher inflation, declining international reserves, and ultimately heightened crisis risk. Khosrosereski and Dashtbani (2024), employing a probit model, identified liquidity growth, exchange-rate acceleration, declining reserves, oil-revenue dependence, and sanctions as the most significant determinants of currency crises in Iran, while real-sector performance and global oil prices mitigate crisis probability.

Finally, Ghobashi et al. (2024) applied Bayesian Model Averaging to rank the non-breakable determinants of currency crises in Iran, showing that variables such as the export-to-output ratio, the exchange-rate gap, inflation, and uncertainty consistently maintain explanatory power across model specifications. Their findings underscore the importance of liquidity imbalances and inflationary pressures in triggering exchange-rate instability and highlight the analytical advantages of Bayesian approaches in addressing model uncertainty.

Research Methodology

The early warning system proposed in this study is designed as a two-stage empirical framework that combines a statistically rigorous variable-selection procedure with a nonlinear crisis-prediction model. In the first stage, a comprehensive set of macro-financial indicators is

screened using Bayesian Model Averaging (BMA) to identify the most robust predictors of currency crises. This stage addresses the pervasive problem of model uncertainty that arises when researchers face a wide set of theoretically plausible explanatory variables.

The second stage utilizes these BMA-selected indicators to estimate a Markov Regime-Switching (MS) model with endogenous transition probabilities, which forms the core predictive component of the system. By allowing transition probabilities to depend directly on macro-financial conditions, the model captures the dynamics of switching between tranquil and crisis regimes.

This two-step architecture improves forecasting reliability by ensuring that the MS model is fed with variables that are both empirically validated and theoretically relevant. A similar two-step logic is applied in the literature on crisis prediction, including recent applications to the Iranian economy such as Ghobashi et al. (2024), which emphasize the value of combining robust variable selection with nonlinear regime-switching techniques.

Bayesian Model Averaging

Selecting relevant indicators is a critical and non-trivial step in constructing currency-crisis early warning systems. Traditional econometric techniques often suffer from model uncertainty, sensitivity to arbitrary variable inclusion, and substantial loss of degrees of freedom when dealing with large sets of explanatory variables. Bayesian Model Averaging (BMA), originally formalized by Jeffreys (1961) and further advanced by Leamer (1978), Raftery et al. (1999), and others, offers a principled solution by accounting for model uncertainty directly in the estimation process.

In BMA, all possible model specifications arising from different combinations of predictors are evaluated, and their posterior probabilities determine the weight each model receives in the analysis. The key output is the Posterior Inclusion Probability (PIP) of each variable, which measures how consistently a variable contributes to explaining the dependent variable across the entire model space. Variables with high PIP values are considered robust predictors, while those with low probabilities are regarded as fragile or non-informative.

This methodology has been shown to be particularly effective in the context of currency-crisis analysis. For example, Feldkircher (2014) demonstrates that BMA successfully extracts robust early-warning indicators from large pools of variables derived from first-, second-, and third-generation crisis models. Likewise, Ghobashi et al. (2024) apply a BMA-based ranking approach to the Iranian economy and emphasize the importance of systematic indicator selection to reduce uncertainty and improve the credibility of crisis-prediction models.

Following this literature, the present study constructs an initial dataset comprising 20 quarterly macro-financial indicators for the period 2001–2021, drawn from theoretical foundations and previous empirical studies. Missing observations were minimal and treated using standard interpolation. To maintain scale consistency and enhance comparability, all variables were transformed into growth rates or ratios before entering the BMA stage.

Table 1- Selected Explanatory Variables for Currency Crisis

Variable Name	SYMBOL	Variable Name	SYMBOL
Inflation	INF	Export to Output Ratio	XPR
Budget Deficit to Output Ratio	BGR	Deviation of Unofficial from Official Rate	ONG

Government Spending to Output Ratio	GGR	Oil Price Changes	OPC
Real Output Growth Rate	RGR	Market Rate Gap Percentage	MEG
Industrial Production Growth Rate	IGR	Growth in Oil Export Revenues	REG
Customs Export Growth Rate	EXG	Exports to Imports Ratio	XIM
Money to Output Growth Rate	MGR	Foreign Exchange Revenue to Foreign Reserves Ratio	FER
Loan to Deposit Ratio	LDR	Foreign Assets to Foreign Debt Ratio (Central Bank)	ALR
Changes in Global Gold Price	GPG	Debt of Banks to Central Bank to Monetary Base Ratio	DML
Uncertainty Index	UNI	Money to Liquidity Ratio	MLR

Source: Research Findings

All of these variables are obtained from the Central Bank's data, and indexation has been carried out. Given that the variables and indices affecting the currency crisis can be divided into two categories: economic and non-economic, the uncertainty index is presented in the non-economic section. The literature on the relationship between uncertainty and exchange rates is limited. To establish a relationship between these two, it is necessary for the uncertainty index to move from a qualitative state to a quantitative one. Despite many studies aimed at quantifying uncertainty, there is no precise definition of economic uncertainty, and most researchers both domestically and internationally have merely introduced substitutes for uncertainty and suggested proxies. Methods of measuring uncertainty (uncertainty indices) can be divided into three categories: uncertainty based on financial markets, uncertainty with predictive ability, and uncertainty based on news or media (Bontempi et al., 2016).

One of the newest types of uncertainty indices based on news and media is the volume of internet search index provided by Google Trends (Pires et al., 2013; Sen & Schmidt, 2011;

Markov Switching Approach

The Markov regime-switching model is a non-linear econometric model designed to analyze time series data whose behavior changes over time. Regime-switching models were first introduced by Quandt (1972) and Goldfeld-Quandt (1973), and then developed by Hamilton (1989) for analyzing and extracting business cycles. This method was particularly used to analyze periods of economic booms and recessions or oscillatory periods in financial markets. In the Markov regime-switching model, it is assumed that the model parameters (such as mean, variance, or other coefficients) will differ depending on the various states or regimes that change over time. These models analyze changes in key variables and can predict potential crises based on changes in economic regimes.

In the regime-switching model introduced by Quandt (1972), the transition mechanisms act independently of each other. However, in the models introduced by Goldfeld-Quandt (1973) and Hamilton (1989), transitions are influenced by a first-order Markov chain. Therefore, these models are known as Markov regime-switching models. This feature allows for more effective

analysis of changes across different economic regimes and a better understanding of the relationship between different states and the transition from one state to another.

In the Markov regime-switching approach, the early warning system (EWS) consists of two main parts: a) A first-order Markov chain, which includes a discrete, unobservable, and endogenous state variable (S_t). In crisis early warning models, this variable includes two states: State 0: which represents the crisis state. State 1: which represents the normal state. While the state variable is not directly observable, it changes over time according to institutional and structural changes, and the behavior of the dependent variable depends on this variable. b) A Markov regime-switching time series model for the dependent variable of interest in the study. This model helps analyze and predict the behavior of the dependent variable and can provide important information about potential turning points or crises. This approach allows for a more detailed examination of interactions between variables and different economic regimes.

The model for this research can be represented by the following equation:

$$\begin{aligned} \text{Equation (1)} \quad EMP_t &= X_t \beta_{s_t} + e_t \quad t = 1, \dots, T \\ e_t &\sim N(0, \sigma_{s_t}^2) \\ \beta_{s_t} &= (1 - s_t) \beta_0 + s_t \beta_1 \\ \sigma_{s_t}^2 &= \sigma_0^2 (1 - s_t) + \sigma_1^2 s_t \\ s_t &= 0 \text{ or } 1 \end{aligned}$$

In this model, EMP represents the percentage change in the currency market pressure index and is the dependent variable of the model. To identify periods of pressure in the foreign exchange market, this study constructs an Exchange Market Pressure Index (EMPI). Following the standard approach proposed by Eichengreen et al. (1996) and Kaminsky et al. (1998), the index combines information from exchange rate movements, international reserves, and interest rate changes. The index is calculated as: $EMPI_t = \Delta e_t - \alpha \Delta r_t + \beta \Delta i_t$

where Δe_t denotes the percentage change in the nominal exchange rate, Δr_t represents the percentage change in international reserves, and Δi_t indicates the change in the domestic interest rate. To prevent any component from dominating the index due to differences in volatility, the weights α and β are defined as the inverse of the standard deviation of each variable.

A currency crisis episode is identified when the value of the EMPI exceeds its mean by more than 2.5 standard deviations. To ensure the robustness of this threshold, sensitivity analyses were also conducted using alternative thresholds of 2 and 3 standard deviations. The results show that the identification of crisis periods remains largely consistent across these alternative specifications, confirming the robustness of the crisis definition used in this study.

X includes leading indicators for the occurrence of a currency crisis and lagged dependent variables, which are determined by Bayesian averaging in the previous section. β represents the model parameters, e_t is the disturbance term, and t indicates time. Due to the unobservable nature of the state variable S_t , it is not possible to precisely determine the prevailing regime at time t . However, using the transition probability matrix, the probability of being in each regime and the probability of transitioning from one regime to another can be obtained.

In this study, it is assumed that the early warning indicators can influence each of the transition probabilities in this matrix, and therefore, these probabilities will be time-dependent. Under these conditions, to estimate the Markov regime-switching model, the joint probability function

between the occurrence of EMP and S_t s is used. Based on the properties of maximum likelihood (ML) functions, the objective is to maximize the probability of the sample occurring in the population, such that the joint probability of the random variables in the sample is maximized.

Thus, based on the joint probability function, the method of maximum likelihood is used to estimate all the random quantities of this model. Of course, all of these considerations will only be suitable for designing the early warning system intended for the research if the data pattern under investigation is nonlinear. Additionally, the disturbance terms of this model must be normally distributed and free from autocorrelation and heteroscedasticity.

If this process is examined in more detail, it should be noted that the unobservable variable in this model follows a first-order two-state Markov chain. Although the state variable is not directly observable, the dependent variable (currency market pressure, denoted by y_t) is as follows:

Equation (2) $(y_t | s_t) \sim N(\mu_{s_t}, \sigma_{s_t}^2)$

Such that both the mean and variance of y_t can change with the regime. The density of y_t conditional on S_t is as follows:

Equation (3) $f(y_t | s_t) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(y_t - \mu_{s_t})^2}{\sigma_{s_t}^2}\right) \quad s_t = 0, 1$

The unobservable switching regime variable changes based on the following transition probability matrix P_t :

Equation (4)

	Zero State		One State	
Zero State	$P_t = \begin{bmatrix} p_{00}^t = \Pr(s_t = 0 s_{t-1} = 0, x_{t-1}) = F(x_{t-1}\beta_0) & \dots & p_{01}^t = (1 - p_{00}^t) \Pr(s_t = 1 s_{t-1} = 0, x_{t-1}) = F(x_{t-1}\beta_1) \\ \vdots & \ddots & \vdots \\ p_{10}^t = (1 - p_{11}^t) \Pr(s_t = 0 s_{t-1} = 1, x_{t-1}) = F(x_{t-1}\beta_0) & \dots & p_{11}^t = \Pr(s_t = 1 s_{t-1} = 1, x_{t-1}) = F(x_{t-1}\beta_1) \end{bmatrix}$			
One State				

Source: Abiad (2003)

where p_{ij}^t is the probability of transitioning from state i at time $t-1$ to state j at time t . F is a cumulative distribution function, which is typically a normal or logistic c.d.f. The elements of the vector x_{t-1} , which is $k \times 1$, are early warning indicators that can influence the transition probabilities. The last element that completes the model is the starting value $p_1^1 = \Pr(s_1 = 1)$, which gives us the unconditional probability of being in state one at time one. Dybvig, Vinberg, and Lee (1994) argue that the handling of this value depends on whether x_t is stationary or not. If x_t is stationary, then p_1^1 is simply the long-term probability of $s_t = 1$, which in turn is a function of β_0, β_1 . If x_t is non-stationary, then p_1^1 is another parameter that needs to be estimated. In practice, if the time series are long enough, the value of p_1^1 has a negligible effect

on the likelihood function, and whether it is calculated as a function of β_0, β_1 , estimated as a separate parameter, or simply considered a fixed value, does not make much difference.

The estimation process used in this study is direct maximum likelihood, with the likelihood function computed using the iteration described in Hamilton (1994). Using the information available up to time t , one can construct $pr(s_t = j | \Omega_t, \Theta)$, which is the conditional (filtered) probability that the t -th observation was generated by regime j , and $j=1,2,\dots,N$ where N is the number of states. These conditional probabilities are aggregated into an $j=1,2,\dots,N$ vector denoted as $\widehat{\zeta}_{t|t}$.

Using the conditional predictive probability of being in regime J at time $t+1$ given the information available up to time t : $pr(s_t = j | \Omega_t, \Theta)$ for $j=1,2,\dots,N$, one can form predictions. These predictive probabilities are aggregated into an $N \times 1$ vector denoted as $\widehat{\zeta}_{t+1|t}$. Finally, it is assumed that η_t represents an $N \times 1$ vector, where the J -th element of it is the conditional density of y_t in equation (2). These predictive and filtered probabilities at each time t are obtained through iterations on the following equations:

$$\text{Equation (5)} \quad \widehat{\zeta}_{t|t} = \frac{(\widehat{\zeta}_{t|t-1} \circ \eta_t)}{1'(\widehat{\zeta}_{t|t-1} \circ \eta_t)}$$

$$\text{Equation (6)} \quad \widehat{\zeta}_{t+1|t} = p'_{t+1} \cdot \widehat{\zeta}_{t|t}$$

P_t is an $N \times N$ transition probability matrix from period $t-1$ to period t , as shown in equation (6), and $\circ$ denotes element-wise multiplication. Equation (5) computes the probability $pr(s_t = j | \Omega_t, \Theta)$ as the ratio of the joint distribution $f(y_t, s_t = j | \Omega_t, \Theta)$ to the marginal distribution $f(y_t | \Omega_t, \Theta)$, where the marginal distribution is obtained by summing the joint distribution over states $1, 2, \dots, N$. Equation (6) implies that once we have our best guess about which state we are in today, it suffices to pre-multiply it by the transpose of the transition probability matrix p_t to obtain the probabilities of being in different states in the future period. Assuming an initial value for parameters Θ and $\widehat{\zeta}_{t|t}$ which in our model is $[1 - P_1^1 \quad P_1^1]'$, we can iterate on (7) and (8) to obtain $\widehat{\zeta}_{t|t}$ and $\widehat{\zeta}_{t+1|t}$ for $t=1, \dots, T$ and $t=1, \dots, T$. The logarithmic likelihood function $L(\Theta)$ can also be computed in this way:

$$\text{Equation (7)} \quad L(\Theta) = \sum_{t=1}^T \log f(y_t | X_t, Y_{t-1}; \Theta)$$

$$\text{Equation (8)} \quad f(y_t | X_t, Y_{t-1}; \Theta) = 1'(\widehat{\zeta}_{t|t} \circ \eta_t)$$

Model Estimation

Determining Variables and Exchange Market Pressure Index

There are three approaches for selecting early warning indicators for crises. In this study, the indicators are reviewed based on a systematic examination of the existing literature, and a total of 20 variables are identified. In addition to the above-mentioned variables, an uncertainty index is also added as a representative of the "psychological (non-economic) factors" section to the list of variables. For this purpose, and given the data limitations in Iran, an approach based on internet search is used. Google provides a search volume index, which indicates the frequency of searches over a specified period and location, normalizing the data on a scale from 0 to 100, where the highest frequency is assigned the value of 100, and other observations are determined relative to that.

To measure the uncertainty index, two steps are taken: In the first step, a list of words related to uncertainty is gathered. In the second step, the frequency of these keywords in Google's database is examined, and keywords are selected to form the uncertainty index. To create the seasonal index, the seasonal values are first summed up and then standardized. The closer the index is to zero, the lower the level of uncertainty, and the closer it is to one, the higher the level of uncertainty. Following the study by Abrishami and colleagues (2016), the word "currency" is selected as the chosen word for extracting the exchange rate uncertainty index in Iran due to its suitable characteristics. The uncertainty index is shown in the graph below.

Additionally, for analyzing currency crises, a dependent variable named "Exchange Market Pressure Index" has been determined. This index is considered as the dependent variable of the model and is calculated based on the study by Eichengreen et al. (1996).

The exchange market pressure index is a weighted average of exchange rate changes, the loss of the country's foreign exchange reserves, and changes in interest rates (Eichengreen et al., 1995). To identify currency crises in this study, the exchange market pressure index of Eichengreen et al. (1995) is used, and its equation is as follows. In this equation, EMP_t represents the exchange market pressure index, e_t is the exchange rate against the US dollar, r_t represents foreign reserves, i_t is the nominal interest rate, $\Delta(e_t)/e_t$ is the standard deviation of relative exchange rate changes, and $(\Delta r_t)/r_t$ is the standard deviation of the change rate in reserves.

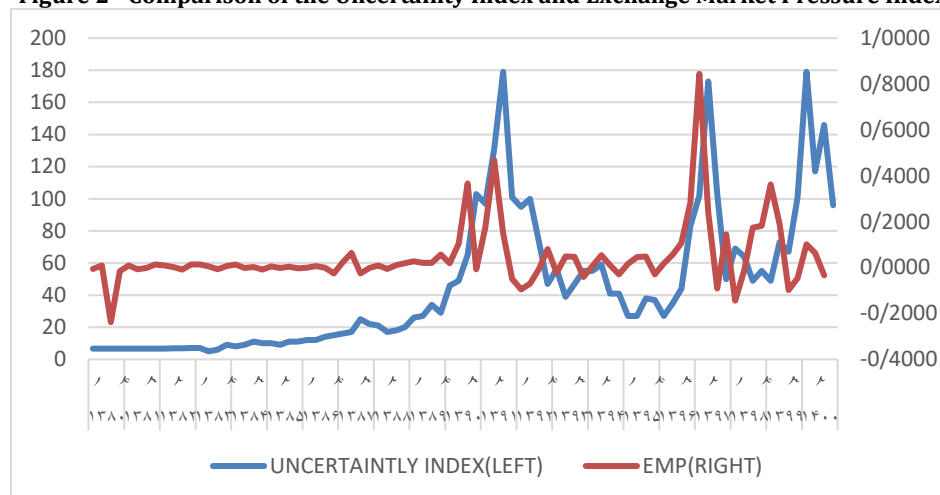
$$EMP_t = \frac{\Delta e_t}{e_t} - \frac{\sigma_e}{\sigma_r} \frac{\Delta r_t}{r_t} + \frac{\sigma_e}{\sigma_i} \Delta i_t$$

After calculating the exchange market pressure index, to identify the dates of currency crises, the index needs to be placed into another model to convert it into a binary series (0 and 1), providing us with the time series of crises. For this purpose, a threshold method can be used, where if the index exceeds 1.5 times the standard deviation plus the mean of the index, a value of 1 is assigned, and otherwise, a value of 0 is assigned. Other values, such as 2 or 3, can also be considered as thresholds.

$\alpha=3$	$\alpha=2.5$	$\alpha=2$	$\alpha=1.5$
Kaminski et al. (1998) Patillo and Berg (1999) Bajona (2008)	Yap (2002) Edison (2003)	Eichengreen and others (1995) Park (2002) Kaminsky and Babson (1999) Bussière and Fratzcher (2006)	Tambunan (2002) Adinin, Setiawati, and Shulya (2002) Tinakorn (2002) Kibritcioglu and others (2001)

Source: Bali et al. (2014)

Empirical studies indicate that the criteria for determining the scope of currency crises differ across economies. In industrial economies with low inflation, a depreciation of the national currency or pressure on the foreign exchange market is recognized as a currency crisis when it reaches 50% compared to the historical trend. However, in developing economies with high inflation, the crisis threshold is determined by deviations more than three times the standard deviation from the historical trend. In Iran, given the high inflation rate, the currency crisis threshold is considered to be 2.5 standard deviations above the historical trend.

Figure 2 - Comparison of the Uncertainty Index and Exchange Market Pressure Index

Source: Research Findings

Results of the Bayesian Averaging Model

Given the uncertainty in determining the variables, this section focuses on identifying the variables that influence exchange rate crises. In this study, no pre-determined model is considered as the correct model; rather, it should be extracted based on the data. Therefore, to clarify the model, the BAS method has been used, and the results confirm the previous method. The five initial models, which have the highest probability of occurrence, can be extracted. The posterior probability of each model is calculated based on Bayes' rule as shown below. This method allows for determining the uncertainty of each model and variable, which is especially important in economic analyses. The various models are simultaneously estimated using the available data, and by comparing the probabilities associated with each variable and model, the best model for prediction and analysis can be chosen. This table includes the results of the model comparison in various criteria, which helps in providing a more precise and transparent analysis of these models. In this way, one model with the aforementioned variables is selected as the model with the highest explanatory power.

Table 3 - Results of the BAS Model

	$P(B \neq 0 Y)$	MOLEL1	MOLEL2	MOLEL3	MOLEL4	MOLEL5
Intercept	1	1	1	1	1	1
XPR	0.99	1	1	1	1	1
ONG	0.34	0	0	0	1	0
OPC	0.38	0	0	0	1	1
MEG	0.83	1	1	1	1	1
REG	0.38	0	0	1	1	0
XIM	0.99	1	1	1	1	1
FER	0.30	0	0	0	1	0
ALR	0.31	0	0	0	1	0
DML	0.37	0	0	0	1	0

MLR	0.93	1	1	1	1	1
INF	0.99	1	1	1	1	1
BGR	0.99	1	1	1	1	1
GGR	0.32	0	0	0	1	0
RGR	0.99	1	1	1	1	1
IGR	0.31	0	0	0	1	0
EXG	0.33	0	0	0	1	0
MGR	0.99	1	1	1	1	1
LDR	0.45	0	1	0	1	0
GPG	0.37	0	0	0	1	0
UNI	0.94	1	1	1	1	1
BF ²	-	1	0.31	0.31	...	0.27
PostProbs ³	-	0.03	0.00	0.00	...	0.00
R ²	-	0.72	0.72	0.72	...	0.72
dim ⁴	-	10	11	11	...	11
logmarg ⁵	-	32.02	30.88	30.88	...	30.73

Source: Research Findings

The results presented in this table indicate that in various models, some variables consistently have a significant and strong impact on the dependent variable. Based on the likelihood of influence, it is clear that variables such as the export-to-output ratio, the percentage gap between the market exchange rate and equilibrium, exports to imports ratio, money-to-money supply ratio, inflation, budget deficit-to-output ratio, real output growth, growth of the money-to-output ratio, and the uncertainty index are significantly influential in most models, as their impact probability

² In Bayesian statistical analysis, "BF" stands for "Bayes Factor." The Bayes Factor is a measure used for model comparison, indicating the strength of evidence in favor of one model over another. When its value is greater than one, it implies that the model has relatively greater explanatory power.

³ In Bayesian analysis, "PostProbs" stands for "Posterior Probabilities." These probabilities specifically represent the likelihood of each model given the observed data after performing Bayesian analysis. In Bayesian modeling, we use a prior probability distribution (Prior Distribution) and the likelihood of the observed data (Likelihood) to calculate the posterior probability distribution (Posterior Distribution). Posterior probabilities indicate how well different models fit the new data.

In the provided table, "PostProbs" refers to the posterior probability for each model, representing the probability that a specific model (such as Model 1, Model 2, Model 3, etc.) is correct or suitable based on the available data. This probability is typically represented as a value between 0 and 1, where the closer it is to 1, the more likely the model is to be correct. These values help identify the models with the highest posterior probability, which can then be used for future predictions or analysis.

⁴ This number could represent the number of parameters used in the Bayesian model. In Bayesian modeling, the number of parameters refers to the variables or factors that are estimated within the model to explain the relationship between the data and the underlying process. The more parameters a model has, the more flexible it is in fitting the data, but it can also lead to overfitting if not properly managed. The number of parameters is an important consideration when evaluating model complexity and ensuring that the model is not too simple or overly complex for the data at hand.

⁵ The logmarg indicates how well the model generally fits the observational data and presents this information in the form of the log of the marginal likelihood. While the value of logmarg cannot be directly interpreted in a straightforward manner, comparing logmarg values across different models helps determine which model is more likely to have generated the data. Higher logmarg values suggest that the model has a greater overall likelihood of explaining the data. This is particularly useful in model comparison, as it provides insight into which model best captures the underlying structure of the data.

is close to 1. This suggests a strong relationship between these variables and the dependent variable, highlighting their importance in various analyses.

On the other hand, other variables do not have a significant impact in some models, or their likelihood of influence is low, indicating that they play a lesser role in explaining the behavior of the dependent variable in these models. Furthermore, the results of various criteria such as R^2 , logmarg, and PostProbs show that models 1, 2, and 3 have the best fit and higher accuracy, while models 4 and 5 are associated with decreasing efficiency and prediction quality. Therefore, based on all criteria, model 1 performs better compared to the other models.

Beyond the statistical identification of relevant variables, the results also provide important economic insights into the determinants of currency crises. Variables with posterior inclusion probabilities close to one—such as inflation, the export-to-import ratio, the gap between the market exchange rate and its equilibrium level, the money-to-liquidity ratio, the budget deficit ratio, real output growth, and the uncertainty index—reflect key macroeconomic imbalances that increase pressure in the foreign exchange market.

High inflation and rapid monetary expansion weaken the purchasing power of the domestic currency and increase expectations of depreciation, thereby intensifying speculative pressures in the foreign exchange market. Similarly, a widening gap between the market exchange rate and its equilibrium level signals the presence of misalignment in the exchange rate, which may trigger corrective adjustments in the form of sharp devaluations.

Fiscal imbalances also play an important role. A higher budget deficit relative to output can increase the need for monetary financing, which in turn accelerates liquidity growth and fuels inflationary pressures. These developments ultimately contribute to instability in the exchange rate market.

External sector indicators such as the export-to-import ratio are also significant. A decline in external balance weakens the country's ability to supply foreign currency to the market and increases vulnerability to exchange rate crises. Finally, the uncertainty index captures shifts in expectations and market sentiment. Higher uncertainty may lead to precautionary demand for foreign currency and intensify exchange rate volatility.

Overall, the consistency of these variables across the highest-probability models indicates the robustness of the results and confirms that macroeconomic imbalances, monetary expansion, fiscal pressures, and uncertainty are among the key drivers of currency crises in the Iranian economy.

Table 4: Non-Breaking Variables Affecting Currency Crises

Variable Name	SYMBOL	Variable Name	SYMBOL
Uncertainty Index	UNI	Export to Production Ratio	XPR
Real GDP Growth	RGR	percentage exchange rate gap from equilibrium	MEG
Growth of Money to Production Ratio	LDR	Exports to Imports Ratio	XIM
Budget Deficit to Production Ratio	BGR	Money to Liquidity Ratio	MLR
Inflation	INF		

Source: Research Findings

Results of Markov Switching Model

The first step in utilizing the time series of the variables in this study for designing an early warning system for currency crises using the Markov regime-switching approach is to determine the degree of cointegration (number of unit roots) of these variables to ensure that spurious regression does not occur. For this purpose, in this study, tests related to stationarity and cointegration are applied. The results obtained from the stationarity test are presented in the table below.

Table 5 - Results of Stationarity Tests

ZA ⁶	ADF	TEST LEVEL	VARIABLE
		Level	Y
		First Difference	
۴.۱۶-	 (۰.۷)	Level	XPR
	 (۰.۰۲)	First Difference	
	 (۰.۶۵)	Level	MEG
	 (۰.۰۱)	First Difference	
	 (۰.۸)	Level	XIM
		First Difference	
		Level	MLR
		First Difference	
		Level	INF
		First Difference	
		Level	RGR
		First Difference	
		Level	LDR
		First Difference	
		Level	BGR
		First Difference	
		Level	UNI
		First Difference	

⁶ The Zivot-Andrews (ZA) test, unlike the ADF and PP tests, does not directly provide a p-value. Instead, it calculates the test statistic, which is then compared with critical values. If the ZA Statistic is smaller (more negative) than the critical value, the null hypothesis is rejected, and the series is considered stationary.

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Source: Research Findings

The results obtained from the Augmented Dickey-Fuller (ADF) test and the Zivot-Andrews test indicate that some variables are stationary at level, and the first-difference of all variables is stationary. Additionally, the results from the Johansen cointegration test confirm the existence of a long-term relationship among the variables. Therefore, under these conditions, the Markov switching regime approach can be applied without the need for any transformation of the variables.

Table 9 - Cointegration Test Results

PROB	TEST STATISTIC VALUE	TEST STATISTIC	TEST TYPE
		eigenvalue	Cointegration Johansen cointegration

Source: Research Findings

Before considering and interpreting the results obtained, it is necessary to test the hypothesis of the appropriateness of the estimated nonlinear model against the hypothesis of linearity of this model. In fact, using this test, we examine whether we have achieved greater explanatory power with the nonlinear model compared to a linear model. For this purpose, the Likelihood Ratio (LR) test proposed by Nag and Beckert (2002) is employed. Based on the results obtained from this test, it can be concluded that at a 99% confidence level, using the nonlinear Markov switching regime approach for estimating the coefficients of the desired early warning system is more appropriate than employing a linear model.

Furthermore, as shown in the table below, based on the results, the disturbance terms of the designed model are normal and free from autocorrelation.

Table 10 - Diagnostic Tests for the Early Warning Model of Currency Crises

PROB	TEST STATISTIC VALUE	TEST STATISTIC	TEST TYPE
		Chi-square with degrees of freedom(10)	Autocorrelation Ljung-Box test
		Chi-square with degrees of freedom(7)	Normality Jarque-bera test

Source: Research Findings

After confirming the appropriateness of the diagnostic tests, the results obtained from estimating the coefficients of the early warning system for currency crises in Iran, during periods of calm and crisis (states 0 and 1), based on the Markov switching regime approach, can be observed in the table below.

Table 8 - Results of Model Estimation in Regime Zero

PROB	T-STATISTIC	STANDARD DEVIATION	COEFFICIENT	EXPLANATORY VARIABLES
0.000	-2.90	0.29	0.85	AR(1)
0.63	0.48	0.78	-0.38	XPR
0.000	3.50	0.15	0.54	MEG
0.000	-4.50	0.10	-0.44	XIM

0.02	-2.30	0.42	0.97	MLR
0.000	3.70	1.50	5.50	INF
0.79	0.27	1.20	0.31	BGR
0.000	3.20	1.60	-5.10	RGR
0.000	4.10	0.51	2.10	LDR
0.000	3.00	0.00	0.00	UNI

Source: Research Findings

Table 9 - Results of Model Estimation in Regime One

PROB	T-STATISTIC	STANDARD DEVIATION	COEFFICIENT	EXPLANATORY VARIABLES
0.19	1.31	0.09	0.12	AR(1)
0.000	5.41	0.37	-1.99	XPR
0.000	3.25	0.06	0.21	MEG
0.000	-5.77	0.05	-0.29	XIM
0.000	-5.56	0.14	0.79	MLR
0.25	1.16	0.43	0.50	INF
0.000	2.95	0.35	1.02	BGR
0.01	2.70	0.29	-0.78	RGR
0.17	1.38	0.12	0.16	LDR
0.31	1.01	0.00	0.00	UNI

Source: Research Findings

It should be noted that in this case, to determine the optimal number of lags for the dependent variable and other variables and to select the most appropriate model, the Akaike Information Criterion (AIC) has been used. The model chosen for the research has the lowest value of this criterion among all other options.

According to the estimated model, it can be observed that the lag variables such as the exchange market pressure index, the percentage gap between the market rate and the equilibrium rate, inflation, budget deficit to GDP ratio, money-to-GDP ratio, and the uncertainty index during periods of stability have significant positive (increasing) effects on the exchange market pressure index and amplify the likelihood of currency crises during the studied time period. On the other hand, the variable of export-to-import ratio during periods of stability has a significant negative effect on this index and, in other words, helps prevent currency crises.

Moreover, based on these results, if a currency crisis occurs, variables such as the percentage gap between the market rate and the equilibrium rate, inflation, the budget deficit to GDP ratio, money-to-GDP ratio growth, and the uncertainty index with positive and significant effects on the exchange market pressure index will exacerbate such crises. However, in the event of a currency crisis, the export-to-import ratio will help improve the crisis situation.

In addition, as shown in the table (unit root test, etc.), most of the coefficients related to the lags of the exchange market pressure index in both regimes (especially in the crisis period) are significant. These significant coefficients may contain crucial information about the effects of the exchange rate system and the changes in it (for example, the implementation of a pegged exchange rate and the central bank's ability to maintain it) on the occurrence of currency crises.

It is also worth mentioning that the effect of the leading indicators examined during the periods of stability and crisis is asymmetric. Additionally, based on these results, it should be noted that the variance of the error term differs between the two regimes, with the variance in the stability period being lower compared to the crisis period.

Based on the calculated probabilities for a currency crisis, the table below shows the years in which each regime occurred, or in other words, the years of a currency crisis and the periods of stability in the Iranian economy.

Table 13 - Periods of Currency Crisis and Stability Periods in the Iranian Economy

PERIODS OF CRISIS AND STABILITY	REGIME
1380(4) 1389(3) 1390(3) 1391(1) 1391(2) 1391(3) 1392(3) 1397(1) 1397(4) 1398(2) 1398(3) 1398(4) 1399(1) 1399(2) 1399(3) 1399(4) 1400(1) 1400(2)	Regim Zero (Critical Condition)
1380(2) 1380(3) 1381(1) 1381(2) 1381(3) 1381(4) 1382(1) 1382(2) 1382(3) 1382(4) 1383(1) 1383(2) 1383(3) 1383(4) 1384(1) 1384(2) 1384(3) 1384(4) 1385(1) 1385(2) 1385(3) 1385(4) 1386(1) 1386(2) 1386(3) 1386(4) 1387(1) 1387(2) 1387(3) 1387(4) 1388(1) 1388(2) 1388(3) 1388(4) 1389(1) 1389(2) 1389(4) 1390(1) 1390(2) 1390(4) 1391(4) 1392(1) 1392(2) 1392(4) 1393(1) 1393(2) 1393(3) 1393(4) 1394(1) 1394(2) 1394(3) 1394(4) 1395(1) 1395(2) 1395(3) 1395(4) 1396(1) 1396(2) 1396(3) 1396(4) 1397(2) 1397(3) 1398(1) 1400(3) 1400(4)	Regim One (Calm Condition)

Source: Research Findings

As can be seen from the table above, the designed system has successfully identified the years of economic crises in Iran. The table below shows the characteristics of each of the two regimes in question. Based on these results, Regime One is more stable than Regime Zero because, when the country's economy is in a calm condition, this period will last on average for 4 seasons. However, if the economy faces a currency crisis, the crisis period will last on average for 1.125 seasons. Furthermore, with a probability of 78.04%, the country's economy will be in a calm condition (16 regime changes have occurred).

Table 14 - Characteristics of Regimes Zero and One in the Early Warning System for Currency Crises

NUMBER OF SEASONS CATEGORIZED WITHIN EACH REGIME	NUMBER OF SEASONS CATEGORIZED WITHIN EACH REGIME	NUMBER OF SEASONS CATEGORIZED WITHIN EACH REGIME	
1.125	21.95%	18	Regime Zero
4.00	78.04%	64	Regime One

Source: Research Findings

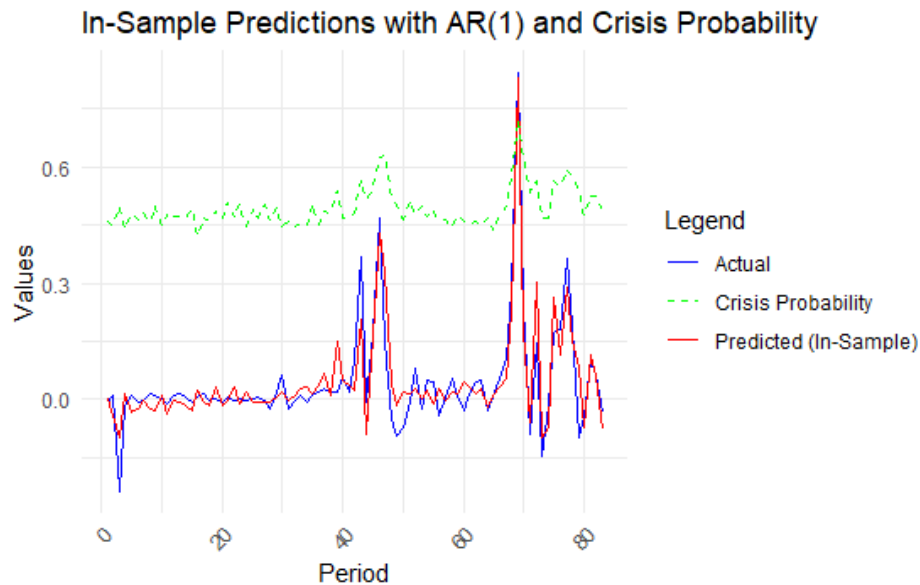
The table below shows the probability of staying in a regime as well as the probability of transitioning from one regime to another. As can be seen from this table, Regime One is more stable than Regime Zero, because if the economy is in Regime One, the probability of staying in this regime is 87%, and the probability of transitioning to Regime Zero is 13%. On the other hand, if the economy is in Regime Zero, the probability of staying in this regime is over 55%, and the probability of transitioning to Regime One is around 45%.

Table 15 - Transition Probabilities from One Regime to Another

REGIME ONE	REGIME ZERO	
0.45	0.55	Regime Zero
0.87	0.13	Regime One

Source: Research Findings

Figure 3 - In-Sample Predictive Performance of Early Warning Systems

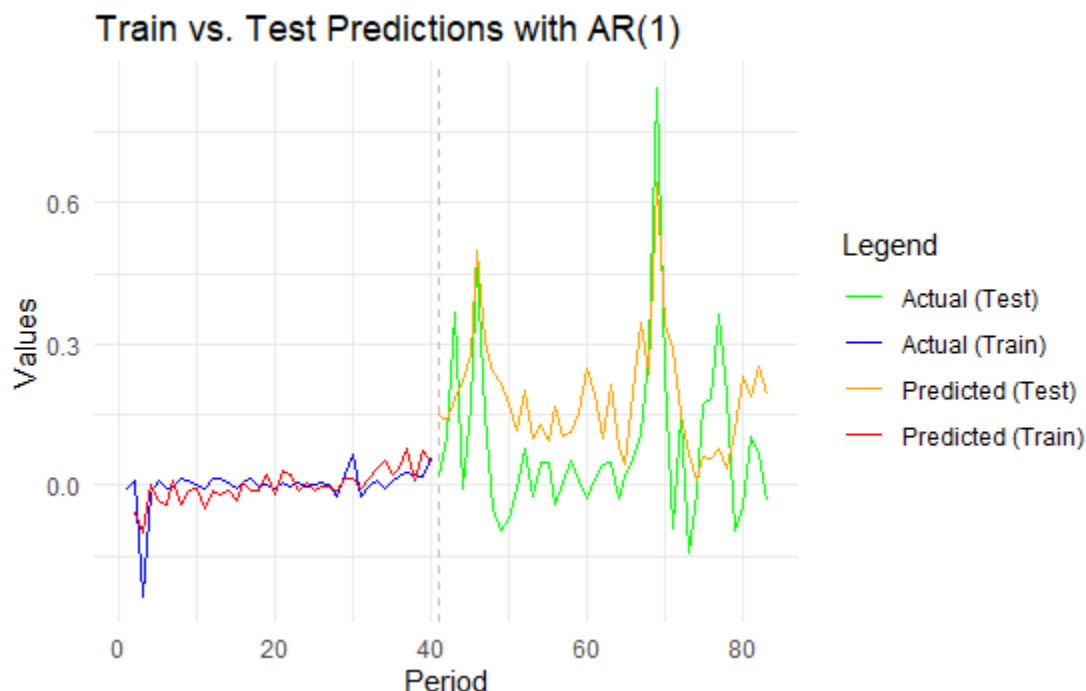


Source: Research Findings

To evaluate the predictive performance of an early warning system, the predicted values of the system's dependent variable must be compared with the actual values. As can be seen from the above chart, this model demonstrates a good in-sample predictive performance, successfully forecasting the fluctuations and currency crises in the Iranian economy. Based on this, the chart below shows the probability of a currency crisis occurring in each of the studied years. According to this chart, when the calculated probability of a crisis exceeds the 50% threshold, a warning of a potential currency crisis is issued.

Finally, an attempt was made to assess the out-of-sample predictive performance of this model. To do this, the model was initially trained on a shorter time period (the 40th season), and after predicting the dependent variable values until the end of the period, the predictive performance of the model was evaluated. The results of this assessment can be seen in the chart below.

Figure 5: Out-of-sample prediction performance of early warning systems.



Source: Research Findings

As can be seen from this chart, the early warning system has successfully predicted the currency crises of 2012 and 2018, as well as the fluctuations in the currency market following these crises. In this context, the results presented above indicate that the designed system has significantly explained the determining factors of currency crises in Iran and has shown a high ability to identify these crises during the analyzed period. Furthermore, this system is expected to perform well in predicting future currency crises. The results show that as the learning periods of the model increase, its ability to explain and predict currency crises improves.

Discussion and Conclusion

Currency crises in Iran are driven by the confluence of domestic imbalances, structural rigidities, and external shocks. This study develops a two-stage early warning system (EWS) that integrates Bayesian Model Averaging (BMA) for robust variable selection with an endogenous Markov Regime-Switching (MRS) model to capture nonlinear crisis dynamics.

The first-stage BMA results reveal four dominant leading indicators with Posterior Inclusion Probabilities (PIP) exceeding 0.90: the exchange rate gap, liquidity growth relative to output, the fiscal deficit ratio, and a Google Trends uncertainty index. Among these, the exchange rate gap plays the most critical role; significant deviations of the market rate from equilibrium sharply increase the probability of transitioning into a crisis regime.

The empirical findings from the MRS model highlight clear structural patterns in regime dynamics. Between 1380 and 1400, the economy spent 18 quarters in the crisis regime (Regime 0) and 64 quarters in the tranquil regime (Regime 1), corresponding to 22% and 78% of the sample period, respectively. Stable regimes exhibit an average duration of 4.0 quarters with an

87% stay probability, whereas crisis episodes are sharp and transient, averaging 1.13 quarters with a 55% stay probability and a 45% recovery probability. The model accurately isolates major historical crisis clusters, particularly 1389–1392 (2010–2013) and 1397–1400 (2018–2021). Both in-sample and out-of-sample evaluations—using the initial 40 quarters as the training set—confirm high predictive accuracy, successfully signaling the 2012 and 2018 collapses when crisis probabilities breached the 50% threshold.

These empirical insights yield critical policy implications grounded in structural trade-offs. First, artificially suppressing the exchange rate under sanctions and reserve constraints intensifies misalignments; aligning market rates with economic fundamentals significantly lowers long-term crisis risks despite short-term adjustment costs. Second, the strong predictive power of fiscal deficits and liquidity growth underscores the vulnerability of debt-monetization regimes, showing that even incremental fiscal-monetary discipline reduces the likelihood of switching to crisis states. Third, because heightened uncertainty drives speculative shifts, enhancing central bank transparency and regular data dissemination can anchor expectations and reduce volatility.

Finally, while the analysis is constrained by quarterly data and unobserved high-frequency capital flows, future research can extend this framework by integrating mixed-frequency models and high-resolution sentiment indicators. In summary, the combined BMA-MRS framework provides a reliable, theoretically anchored EWS that enables policymakers to identify emerging currency vulnerabilities and evaluate structural policy trade-offs effectively.

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