Journal of Algorithms and Computation

journal homepage: http://jac.ut.ac.ir

A Note on Early Warning Systems for Monitoring the Inflation of Iran

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ABSTRACT

To check the financial stability, it is important to alarm the possibility of future potential financial crisis. In the literature, the early warning system (EWS) is designed to warn the occurrence of a financial crisis before it happens. This tool gives strengthens to managers to make efficient policy in real economic activities. Hyperinflation, as a financial crisis, is an uncommon bad phenomenon in every economy. It quickly erodes the real value of the local currency, as the prices of all goods increase. This causes people to minimize their holdings in that currency as they usually switch to more stable foreign currencies, often the US Dollar. Hence, designing a EWS for detecting hyperinflation is valuable task. In the current paper, Iran monthly inflation is modeled by a first

ARTICLE INFO

Article history:
Received 12, July 2019
Received in revised form 17, March 2020
Accepted 28 April 2020
Available online 01, June 2020

Keyword: Economic crisis, EWS, MS model, Logistic regression.

AMS subject Classification: 62P10.

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1 Abstract continued

orders autoregressive and moving average model (ARMA) with two-state Markov switching (MS) states, i.e., $MS\,(2) - ARMA\,(1,1)$. Based on this model, a logistic-EWS is proposed. From the empirical results, it is seen that, in Iran, the low inflation state is more probable than state of high inflation. Beside this, the time of remaining in the low inflation position is almost 9 times more than of high inflation position. To check validity of the results and control prediction errors, it is seen that at least 89 percentages of future states of inflation are correctly predicted with a low noise-to-signal ratio discrepancy measure.

2 Introduction

One of the main goals in each economy is reaching to the stability in almost all financial and monetary sectors. This type of stability is referred as economic stability. Inflation is a key macroeconomic variable that gives the overall image of economy in each country. It also closely relates to the other variables such as the gross domestic product (GDP) and unemployment rate. These factors also have their own impacts on the state of economy by imposing their effects on the inflation. The inflation, directly, is defined as the percentage change of consumer price index (CPI). Inflation crises are considered a s hyperinflation (high inflation) events (see, Rohn *et al.* 2015). Generally, economists assign the term of hyperinflation to any economy when its monthly inflation rate is greater than 50 percentages. Hyperinflation phenomenon, in addition to the depreciation of national money, has inappropriate effects on efficiencies of different financial markets. Hence, policymakers should monitor the inflation fluctuations and find a mechanism to warn early such crises. This monitoring leads to the economic stability, ultimately. On the other hand, managing all types of risks in hyperinflationary situations necessarily has a direct relationship to the economic policy. Thus, it is a time-consuming procedure and its results may have conflicts with the result of other monetary policies. So, true foreknowledge about the inflationary situation plays a key role in economics and helps to reach the better economic growth (see Kamps *et al.*, 2014).
In any time, economic crises make concerns for the world. During the last decades, many countries have been faced with economic crises that caused bad significant economic consequences. Some of them were happened in European countries, Japan and in some of the Nordic countries during years 1992-1993. Empirical results of other crises such as Mexican crisis during1994-1995, Asian financial crisis throughout 1997-1998, and Russian crisis at 1998 showed that vulnerability can cause instability in financial sector (Bhattacharya, 2009). As Basu *et al.* (2017) mentioned the inflation is one of economic factor which causes financial crises, especially in Iran as a developing country. Hence, it is natural to investigate the way to alarm the crises before their occurrence since managing the unstable economy after any kind of crises is a costly procedure and sometimes it is an impossible task. The necessity of reducing crises vulnerability shows that there is need for finding the effective early detection system. Early warning of emerging vulnerabilities

may help policymakers to avoid facing crises by making suitable decisions soon to prevent losses in real economic activities. Some methods apply statistical methods to indicate a vulnerable situation through the EWS. The EWS could model the extreme events using statistical methods and information from the past (Casu *et al.*, 2011).
In financial stability literature, it is important to design a mechanism to compute the probability of the crises events over specific time horizon. The signal-based models may prepare the indication tools for this purpose. There are many methods for inflation monitoring. One of them is composite leading indicator which is based on different macro-variables to reveal the inflation cycle. In monitoring inflation, one of the recent methods for studying about the inflation trend is to use the EWS (see, Lang *et al.* (2018). It can help in detecting the unusual trend in inflation. The main goal of EWS is to predict crises with negative impact in different environments. In economics, these models are developed since the end of the 19^{th} century and help to avoid undesirable events. Indeed, EWS alerts before the occurrence of a crisis. This provides time for authorities to implement essential policies to prevent the effect of bad events (Machuca, 2017).
The EWS is able to quantify the probability of hyperinflation crisis occurrence in the future. In this way, policymakers can benefit from the results in assessing inflation risks in financial activities. This method helps us to manage efficiently the overall economy and leads to reach the general equilibrium in different markets. So, missing the alarms from the inflation trend can cause the misunderstanding of the current real economy situations. In practice, monitoring the inflation is exactly the implicit study of almost all macroeconomic variables. Inflation is arising from the continuous increases in price level which can cause the depreciation in purchasing power and economic disorders (see, Lang *et al.* (2018). In practice, it is useful to construct EWSs based on all economic variables related to inflation, like interest rate, liquidity, unemployment rate and also all kind of the financial risks. In real situations, the crisis detection is too difficult procedure, like forecasting models during last decades. This difficulty is related to the features of EWS and its accuracy of the crisis detection. It is possible to use a large set of potentially informative variables that their effects depend on the occurrence of crises (Candelon *et al.*, 2010).
Bussier and Fratzscher (2008) indicated the optimal model for policymakers in risk management and estimated the probability inflation crisis by extracting warning signals. Casu et al. (2011) set the threshold value at a certain multiple of standard deviations from the indicator's long-run mean. Again, such dynamic choice of the threshold value does really address the main issue as it is expected to be dependent on the sample properties. There are other methods of constructing a EWS model including Rose and Spiegel (2012) used a multiple indicator multiple cause approach. Many central banks and international organizations have developed EWS models which are aimed at anticipating the timing of a financial crisis and ensuring the safety of the financial system, see Frankel and Saravelos (2012).
Duca and Peltonen (2013) presented an assessment tool for early detection of systematic risks during financial crises. They used financial stress index and family of discrete choice models. They showed that the combination of domestic and global macro-financial

vulnerabilities improves the ability of models in forecasting procedure. EWS also can be developed to identify the impact of domestic and external factors in emerging market crises. Savona and Vezzoli (2015) proposed a new algorithm for regression tree models to obtain predicted probabilities for each country. Furthermore, Markov switching models have been also used to draft EWS models. Rohn *et al.* (2015) studied economic resilience from a new set of vulnerability indicators for OECD (Organisation for Economic Co-operation and Development) countries. Kamps et al. (2015) identified fiscal and macroeconomic imbalances-unexploited synergies under the strengthened EU governance framework. Basu *et al.* (2017) argued that fiscal, balance of payment and economic crises may respond to different causes, and, hence justifying design of specific EWS for each type of crisis.

Machuca (2017) analyzed the determinants of balance of payment crisis in Euro area economies. Abdelsalam and Abdel-Latif (2018) developed an optimal early warning system for financial crises in developing countries under model uncertainty. To this end, they assessed a number of EWS tools of financial crises with the aim of proposing an optimal model that can predict the incidence of a currency crisis in developing countries. Then, they employed the dynamic model averaging and equal weight approaches to combine forecasts from individual models allowing for time varying weights. Lang *et al.* (2018) proposed a framework for early-warning modelling with an application to banks. Their framework had optimal out-of-sample forecasting properties and is applied to predicting distress in European banks. Minguez and Carrascal (2019) summarised the findings obtained in the estimation of an economic crisis early warning model for the euro area countries. Their findings showed that monitoring five variables that may indicate the emergence of macro-financial imbalances-current account balance, unit labour costs relative to the rest of the euro area, household indebtedness, corporate indebtedness and sovereign risk premium. Their results facilitate the early detection of downturns in the euro area countries.

The aim of this paper is to find an efficient EWS model for waning inflation crisis. It is based on MS models for monthly percentage change of inflation of Iran in order to reduce vulnerability caused by hyperinflation. The paper then uses the producer price index (PPI) as another macroeconomic indicator which has leading properties for switching between inflation regimes. The end-goal of the paper is to develop models that can quantify the possibility of the future occurrence of high inflation. The rest of paper is designed as follows. In section 2, an appropriate MS model is introduced and after model checking, based on real data set, the logistic approach prepares the mentioned EWS. Finally, the forecasting performance of EWS model will be checked by using the in-sample and out-sample methods. Section 3 concludes.

2 Modelling and empirical results. Consider a two-regime $MS - ARMA$ model in which the transition is driven by a two-state Markov chain. Let Y_t be the monthly inflation rate time series. Assume that y_t follows a two-regime $MS\,(2) - ARMA\,(p, q)$ model (see, Lang *et al.*, 2018),

$$E\left(y_t|Y_{t-1},s_t\right)=\left\{\begin{array}{lr}\alpha_0+\sum_{i=1}^{p}\alpha_i y_{t-i}+\sum_{j=1}^{q}\beta_j z_{t-j}, & if \quad s_t=0,\\ \alpha_0^*+\sum_{i=1}^{p}\alpha_i^* y_{t-i}+\sum_{j=1}^{q}\beta_j^* z_{t-j}, & if \quad s_t=1.\end{array}\right)$$

Here, $Y_{t-1}=(y_1,\ldots,y_{t-1})$ (throughout this section, bold letters are vectors) and $s_t=1$ indicates the hyperinflation of economy. As soon as, unknown parameters $\alpha_i,\alpha_i^*,i=0,\ldots,p$ and β_j and $\beta_j^*,j=0,\ldots,q$ are estimated, then this model reveals the features of the inflation in crisis states ($s_t=0$). The probability transition matrix of the Markov chain is:

$$P=\begin{bmatrix}p_{00} & p_{10}\\ p_{01} & p_{11}\end{bmatrix}$$

where $p_{ij}=P\left(s_t=j|s_{t-1}=i\right),i,j=0,1,$ are elements of matrix. Unknown orders (p,q) are estimated using extended autocorrelation function approach (EACF). After verification and model checking such as calibration, the output of final MS model provides a state variable for logistic regression as the EWS method.

Based on the nature of logistic regression, it is possible to build model for the state variable and predict the inflation regime (low inflation and high inflation or inflation crisis. Let $p_0^t=P\left(s_t=0|Y_{t-1}=y_{t-1},\ X=x\right)$. Here, X stands for some exogenous variables. Then, the logistic regression is defined as:

$$Logit\left(p_0^t\right)=log\left(\frac{p_0^t}{1-p_0^t}\right)=\gamma_0+\gamma^T x$$

where T stands for transpose operator and γ_0 , γ^T are unknown parameters which are estimated using the maximum likelihood method (Agresti, 2013).

The data set consist of 22 years of monthly percentage change of Iran CPI from May 1997 to October 2018 taken from Economic Time Series Database (ETSD) of Central Bank of Iran (CBI). Seasonal adjustment (SA) is done using *X-12 ARIMA* software. The SA valued of Iran inflation is plotted in Figure 1.

Visually, time series of inflation seems to be stationary in mean. First, Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test shows monthly inflation does not have deterministic trend. However, the stationary test (Philips-Peron test) implies that there is not any significant non-stationary in time series. Also, the nonlinearity test (Teraesvirta test) indicates that that linearity hypothesis is rejected suggesting that the nonlinearity effects should add to the linear parametric model. All tests are
done using the *R* software. Interested readers should notice that the null hypothesis of stationary test implies that the SA valued of monthly inflation has unit root.

Again, checking the Figure 1, it is seen a negligible volatility clustering pattern among the time series.

The model checking procedure highlighted that there is no heterogeneous effect in variance structure and autocorrelation effect in residual time series.

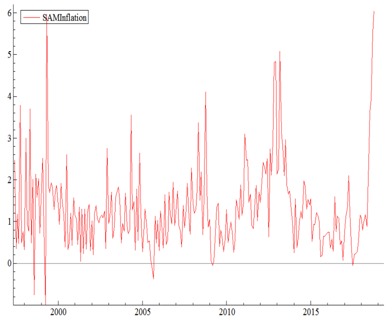

Figure 1: SA-valued of Iran Monthly Inflation. May 1997-October 2018

Table 1: Diagnostic Tests

Test	Stat.	Sig.
Stationary	-200.56	0.01
Nonlinearity	22.082	1.60e-05

2.1 MS model identification. The unknown parameters of MS model are estimated using *OxMetrics* software. Through the EACF results (Table 2), a two-state Markov switching $ARMA(1,1)$ is the best fitness among other candidates. Notations x and o stands for good and bad fitness of model with specified orders p, q .
Indeed, the EACF results suggest $p = 1$ and $q = 1$ gives the best small appropriate model. Hence, the model is given as follows:

$$y_t = \begin{cases} \alpha_0 + \alpha y_{t-1} + \beta z_{t-1} + z_t, & s_t = 0 \\ \alpha_0^* + \alpha^* y_{t-1} + \beta^* z_{t-1} + z_t, & s_t = 1 \end{cases}$$

where y_t is monthly inflation and z_t is a white noise process refers to the moving average part of the time series. Table 3 gives the parameter estimates of selected model. It is seen that all parameters are significant and the variance of white noise z_t is 0.04 which shows the accuracy of estimates.
Hereafter, transition probabilities are estimated. Based on the transition probabilities of the MS model (Table 4), the probability that the economy shifts from the "high inflation" state to the "low inflation" state ($p_{01} = 0.69$) is about 13 times the probability of shifting from the low inflation regime to a high regime ($p_{10} = 0.05$). Smoothed transition probabilities are plotted in Figure 2. These probabilities are used to segment months of study to the "high inflation" and "low inflation" states. Also, Table 5 (derived by *Oxmetrics* software) presents duration of remaining in specified states. The expected duration of low inflation is estimated as 18.31 months while that time for high inflation is about 1.38 months. This fact implies that, on average, once the Iran economy enters to "high inflation" state, it stays in that state for about 2 months.

Table 2: Estimation Results of the EACF

		q						
		0	1	2	3	4	5	6
p	0	0.260 (x)	0.207 (x)	0.281 (x)	0.175 (x)	0.047 (o)	0.159 (x)	0.112 (o)
	1	-0.464 (x)	-0.060 (o)	0.138 (x)	0.085 (o)	-0.101 (o)	0.111 (o)	0.010 (o)
	2	-0.498 (x)	-0.430 (x)	0.125 (o)	0.072 (o)	-0.173 (x)	0.117 (o)	0.018 (o)
	3	-0.305 (x)	0.311 (x)	-0.313 (x)	0.078 (o)	-0.087 (o)	0.012 (o)	0.053 (o)
	4	0.483 (x)	-0.026 (o)	-0.213 (x)	-0.174 (x)	-0.063 (o)	0.016 (o)	0.113 (o)
	5	0.479 (x)	-0.088 (o)	-0.214 (x)	-0.021 (o)	-0.079 (o)	0.014 (o)	0.041 (o)
	6	-0.126 (o)	-0.085 (o)	-0.138 (x)	0.038 (o)	-0.077 (o)	0.030 (o)	0.043 (o)

Table 3: Estimation Results of a two-state MS-ARMA(1,1)

State	Parameter	Estimate	Standard Error	t-statistics	Sig.
State 0 (High Inflation)	α_0	3.9375	0.2936	13.4	0.000
	α	1.2974	0.1186	10.9	0.000
	β	-0.4038	0.1622	-2.49	0.013
State 1 (Low Inflation)	α_0^*	1.7953	0.3465	5.18	0.000
	α^*	0.6988	0.1038	6.73	0.000
	β^*	-0.3985	0.1256	-3.17	0.002
	log-likelihood	-307.43671			

Table 4: Transition probabilities of the two-state MS-ARMA(1,1)

Low Inflation at time t	High Inflation at time t	
0.05	0.31	High Inflation at time t+1
0.95	0.69	Low Inflation at time t+1

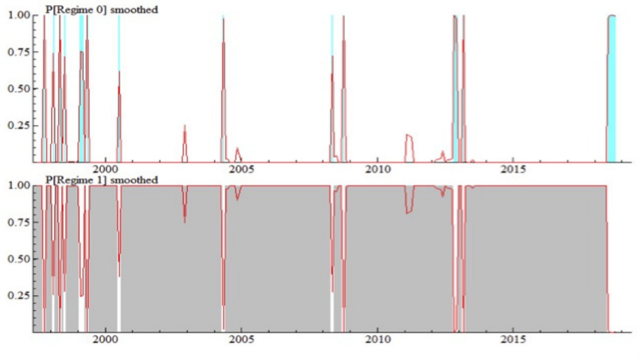

Figure 2: Smoothed probabilities for each stat

Table 5: Regime classification based on smoothed probabilities

Low Inflation (State 1)			High Inflation (State 0)		
Mean Probability of Event	Duration	Period	Mean Probability of Event	Duration	Period
1.000	3	1997(7) - 1997(9)	1.000	1	1997(10) - 1997(10)
1.000	3	1997(11) - 1998(1)	0.743	1	1998(2) - 1998(2)
0.998	2	1998(3) - 1998(4)	0.999	1	1998(5) - 1998(5)
0.992	1	1998(6) - 1998(6)	0.720	1	1998(7) - 1998(7)
0.996	6	1998(8) - 1999(1)	0.751	2	1999(2) - 1999(3)
1.000	1	1999(4) - 1999(4)	1.000	1	1999(5) - 1999(5)
1.000	13	1999(6) - 2000(6)	0.619	1	2000(7) - 2000(7)
0.994	45	2000(8) - 2004(4)	0.978	1	2004(5) - 2004(5)
0.995	47	2004(6) - 2008(4)	0.723	1	2008(5) - 2008(5)
0.980	4	2008(6) - 2008(9)	0.996	1	2008(10) - 2008(10)
0.984	48	2008(11) - 2012(10)	0.988	2	2012(11) - 2012(12)
1.000	2	2013(1) - 2013(2)	1.000	1	2013(3) - 2013(3)
1.000	63	2013(4) - 2018(6)	0.994	4	2018(7) - 2018(10)

Table 6: States description

Monthly inflation mean	percentage of months assigned to each state	Number of months assigned to each state	Expected duration	State
3.85	7.03%	18	1.38	High Inflation (State 0)
1.1	92.97%	238	18.31	Low Inflation (State 1)

Table 7: Estimated Logistic Model

Parameter	Coeff.	Std. Error	Wald Chi-Square	df	Sig.
γ_0	-3.883	0.4787	65.813	1	0.000
γ	0.601	0.1795	11.221	1	0.001
LR stat.	20.852				
sig (LR stat.)	0.000				

From Table 6, it is seen that, the estimated duration of staying economy in "low inflation" position is about 19 months which is 9 times more than that duration of "high inflation" state.

2.2 Logistic regression. In this section, the logistic regression model is applied to define a EWS for detecting the high inflation pattern in Iran. The probabilities resulting from the logistic model could prepare a better assessment about the possibility of inflation crisis in Iran. Based on the regime classification from the MS model (Table 5), an episode of high inflation is tagged 0 while an episode of low inflation is labelled as 1. The estimated logistic regression is given in Table 7. The signs of the coefficients of crisis indicators are consistent with theoretical expectations. The percentage change in PPI index is associated positively with the probability of high inflation state. This fact implies that a surge in the values of PPI, as a leading indicator, increases the probability of entering to "high inflation" regime. It is worth noticing that the role of PPI is significant in the final model (its coefficient is significant, statistically) and its coefficient is correct, based on economical theory. The estimated logistic regression is:

$$Logit\left(p_0^t\right) = -3.883 + 0.601 PPI_t$$

This means that one percentage increase in PPI leads to increase of 0.601 in the probability of the inflation crisis.

Although, inflation in Iran is affected by various factors such as oil prices, political factors, sanctions, and so on. However, in this section, because of following arguments, the PPI

Table 8: Definitions of A,B,C,D

Name	Definition
A	The model indicates a crisis when a high inflation event indeed occurs.
B	The model indicates a crisis but high inflation does not occur.
C	The model does not signal a crisis but a crisis in fact occurs.
D	The model does not predict a crisis and no crisis occurs.

variable is only used to derive the EWS tool: (a) This paper uses a price index (PI) (which is a microeconomic sight) perspective to the problem of EWS for financial crises. This is why, it uses two main PI's, i.e. CPI and PPI. (b) Clearly, the effect of above mentioned factors are seen in jumps of CPI and PPI, indirectly. (c) In the field of EWS, in spite of regression analysis, researchers search for an appropriate simple model (sometimes based on expert prior opinion) to construct EWS. It is enough, the EWS has a perfect in-sample-out-of-sample results (see sub-section 2.3) to detect the crises early. Complex models have two bad features for building EWS, (although, sometimes they have good regression fitness). First, all variables should be observed and a simple missing observation of a variable fails the alarming of a EWS. Second, they need statistical requirement such as normality and checking the co-linearity which is a time-consuming work. Also, notice that, a mistake in computation in complex models (which occurs frequently) makes risk of modelling for EWS.

2.3 Evaluation of EWS. To assess the accuracy of presented EWS, the following performance criteria suggested by Duca and Peltonen (2013) are computed:
(a) Percentage of crisis correctly called (PCCC): $\frac{A}{A+C}$,
(b) Percentage of non-crisis correctly called (PNCCC): $\frac{D}{B+D}$,
(c) Percentage of observations correctly called (POCC): $\frac{A+D}{A+B+C+D}$,
(d) Adjusted noise-to-signal ratio (ANSR): $\frac{\left(\frac{B}{B+D}\right)}{\left(\frac{A}{A+C}\right)}$,
(e) Probability of an event of high inflation given a signal (PRGS): $\frac{A}{A+B}$,
(f) Probability of an event of high inflation given no signal (PRGNS): $\frac{C}{C+D}$, and
(g) Percentage of false alarms to total alarms (PFA): $\frac{B}{A+B}$.
Table 8 gives the definitions of A,B,C,D.

Table 9 proposes potentials of presented EWS. Based on the in-sample forecasts, the model is able to correctly predict 14 percentage of high inflation and 99 percentages of low inflation events. Overall, 94 percentage of observations are correctly predicted by the model. Moreover, the probability of a high inflation event is relatively high i.e., 67 percentages while the proportion of false alarms is relatively low i.e., 33 percentages.

In the evaluation of the out-of-sample forecasts, the EWS model is re-estimated using the sample period from May 1997 to April 2017. The aim is to forecast the inflation regimes from May 2017 to October 2018. Results of Table 9 show that the probability of

Table 9: Forecasts of the EWS model

In-Sample		Actual				
		High Inflation		Low Inflation		Total
Model-base	High Inflation	2	(14%)	1		3
	Low Inflation	12		223	(99%)	235
	Total	14		224		238

Out-Sample		Actual				
		High Inflation		Low Inflation		Total
Model-base	High Inflation	2	(50%)	0		2
	Low Inflation	2		14		16
	Total	4		14	(100%)	18

a high inflation event is 100 percentages which is higher than the in-sample percentage. In addition, the proportion of false alarms for the out-of-sample forecasts falls to zero from 33 percentages for the in-sample forecasts.

3 Conclusions. Due to the essence of detecting the vulnerability of economy in future and avoiding financial crises, this paper develops a EWS for predicting the high inflation state in Iran. In order to design an appropriate EWS, a combination of two approaches is considered. First, fitting a MS time series for determining the crisis states and then a logistic regression for computing the probability of crisis events. The output of the regime classification helps researchers to build a logistic regression model.

Empirical results show that Iran inflation is modelled by a two-state MS-ARMA(1,1) process. It is seen that low inflation state is more likely than the high inflation position. The probability of switching from high inflation regime to the low one is 0.31 and switching to the crisis regime from the low inflation occurs with the probability of 0.69. The probability transition matrix estimation also provides the regime classification and expected duration

Table 10: Forecasting Performance of the EWS model

	In-Sample	Out-Sample
PCCC	14.3	50.0
PNCCC	99.5	100.0
POCC	94.5	88.9
ANSR	2.8	0.0
PRGS	66.6	100.0
PRGNS	5.1	12.5
PFA	33.3	0.0

of both regimes. In addition, the estimated duration of low inflation is 9 times more than that probability of high inflation state. The average value of monthly inflation for high regime is more than 3 times that of low state. Results of the EWS forecasts show that at least 89 percentages of states are predicted correctly with low noise-to-signal ratio, as a discrepancy measure. Thus, the presented EWS has some potential as a complementary tool in the CBI's monetary policy formulation based on the in-sample and out-of sample forecasting performance.

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