Review Article

The Phillips curve in Iran: econometric versus artificial neural networks

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A B S T R A C T

In this paper, we develop a function of inflation, unemployment, liquidity and real effective exchange rate by applying Autoregressive Distributed Lag (ARDL) and Artificial Neural Networks (ANN). We employ the aforementioned methods to derive the so-called Phillips curve. For the empirical objective, our primary purpose is explicitly to compare two types of the Phillips curve models obtained by ANN and the econometric methods, ARDL. Then we can check the behavior of the Phillips curve in Iran. We demonstrate that the Phillips curve for the empirical data in Iran differs slightly across ANN than econometric methods. In other words, according to the structure of Iran's economy, the ANN technique outshines the other one in terms of goodness of fit and prognosis capability. Finally, under two scenarios inflation would be forecasted in Iran up to 2025. Our findings point out that the trend of price changes in Iran would have an increasing trend in the considered period.

1. Introduction

Inflation and unemployment are undoubtedly vastly used economic words. The relation between these two key economic variables is explained by the so-called Phillips Curve. Understanding the Phillips Curves in various economic systems is very important for policymakers to keep inflation under control. In 1958, A. W. Phillips found that the correlation between unemployment and the rate of change of money wages in the UK is negative (see Phillips (1958)). Economists after him quickly developed his findings to the other countries.

In pursuing such challenges, the Phillips curve was expanded in different shapes by Samuelson and Solow (1960), Friedman (1968), Phelps (1968), Lucas (1973) and Sargent et al. (1973). These expanded curves have really important signals on the demand side policies especially monetary policies and inflationary analysis. So, different shapes of the Phillips Curve have become more attractive for the economists. In other words, the Phillips curve shape is more charismatic in macroeconomics because of its important signals on the demand side policies. The linear shape supposes a constant slope for the curve. Accordingly, the sacrifice ratio is fixed regardless of the disinflation speed. Diversely, the nonlinear Phillips curve says that the disinflation speed has some effects on the sacrifice ratio. Our primary purpose in this paper is to develop a function of inflation, unemployment, liquidity and real effective exchange rate, which is imperative for policymakers to evaluate the sacrifice ratio that measures the amount of cost needed for decreasing the inflation rate over a period. We reconsider the Phillips curve by using the

non-linear method, which extends the traditional Phillips curve model in one direction: from linearity to nonlinearity.

Using non-classic methods for identification and prediction of complex systems-related problems has been expanded. Artificial Neural Networks (ANN) have become popular for modeling non-linear economic relationships, recently. Using neural networks in economics came back to White (1988). They used this method to predict the IBM daily stock returns. Artificial Neural Networks have been largely used in three classes of applications in economics: classification of economic agents, time series prediction and the modeling of bounded rational agents (see Herbrich et al. (1999)). Moshiri and Cameron (2000) used a Back-propagation Network (BPN) in comparison with six econometric models to predict Canada's Inflation. Furthermore, Chen et al. (2001), Nakamura (2005), Kon and Turner (2005), Aminian et al. (2006) and Choudhary and Haider (2012) illuminate the potential role of ANN in the context of forecasting economic data.

The main aim of this paper is to present a very simple model for the Phillips Curve in Iran using both econometric and Artificial Neural Network (ANN) methods. So, to get a sense of such objectives, the main purposes are, firstly, time series method, ARDL, will be used in this research as one of the recently developed methods against which the performance of other advanced technique, ANN, will be compared. Secondly, checking how the linkage between inflation and unemployment would be up to 2025 by the best estimator (It coincides with the end of Iran's 20-years perspective document).

In order to realize this objective, the paper is organized as follows:

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first, a brief introduction was presented. In the second section, the proposed model is explicitly presented. In the third Section, the model estimations are done, and finally, in the last section, the conclusion will be stated.

2. Main text

The linkage between inflation rate and economic activities such as unemployment characterized by a Phillips curve is investigated broadly. There are different theoretical and empirical methods of considering such a relationship, which yield various policy signals. Despite the significant advances in the theoretical modeling, the Phillips curve is still estimated by the economic conditions of each country. The study is pursued by the framework of the autoregressive distributed lag regression and artificial neural networks.

2.1. The model and methodology

2.1.1. Autoregressive distributed lag (ARDL) and cointegration analysis

We employ the autoregressive distributed lag (ARDL) approach to catch up the inflation behavior in the framework of the Phillips curve in Iran. This approach is originated by Pesaran and Shin (1998) and Pesaran et al. (2001). In comparison with other cointegration methods, the ARDL cointegration approach has numerous advantages: first, the ARDL approach does not require pre-testing variables, which means that the ARDL can be applied irrespective of whether underlying regressors are purely I(0), purely I(1) or mutually cointegrated. The approach is applicable on the existing relationship among variables in levels regardless of their order of integration. Second, the ARDL procedure is the more statistically significant approach to determine the cointegration relation in small samples (Ozturk and Acaravci (2011)), while the other cointegration techniques are sensitive to the sample size. Third, it is impossible in the other cointegration test that the different variables have different optimal lags, while it is possible with the ARDL. To check other advantages in details see, e. g., Odhiambo (2009) and Sankaran et al. (2019).

The ARDL procedure employs a single equation to estimate the long-run relationships among the variables. So, the ARDL model for the functional specification of long-run relationship between inflation and unemployment may follows as:

$$\Delta Linf_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta Linf_{t-i} + \sum_{i=0}^{n} \alpha_{2i} \Delta Lun_{t-i} + \sum_{i=0}^{n} \alpha_{3i} \Delta LM2_{t-i}$$
$$+ \sum_{i=0}^{n} \alpha_{4i} \Delta LRER_{t-i} + \beta_1 Linf_{t-1} + \beta_2 Lun_{t-1} + \beta_3 LM2_{t-1} + \beta_4 LRER_{t-1} + \varepsilon_t$$

(1)

Where

inf, un, M2 and RER respectively stand for inflation rate, unemployment, liquidity and real effective exchange rate. ε_t is white noise term, Δ is the first difference operator and L is related to natural logarithm. The parameters αs denote the short-run coefficients and βs are the corresponding long-run multipliers of the underlying ARDL model.

The bounds testing procedure is based on the joint F-statistic (or Wald χ^2 statistic) for cointegration analysis. The null hypothesis of no cointegration among the variables in Eq. (1) is ($H_0 : \beta_j = 0$) against the alternative hypothesis ($H_1 : \beta_j \neq 0$), $j = 1, 2, 3, 4$. Pesaran et al. (2001) and Narayan (2005) individually report two sets of critical values (CVs) which provide CV bounds for all classifications of the regressors into purely I(1), purely I(0) or mutually cointegrated. The lower CVs refer to the I(0) series and the upper CVs to the I(1) series. If the computed F-test statistic exceeds the upper CV, then the null hypothesis is rejected, indicating cointegration. If the F-statistic falls into the bounds then the cointegration test becomes inconclusive unless we know the order of integration of the underlying regressors. If the F-statistic is lower than the

lower CV, we cannot reject the null hypothesis of no cointegration. The two sets of CVs are reported in Narayan (2005) for sample sizes ranging from 30 observations to 80.

In the next step, if there is an evidence of long-run relationship (cointegration) between variables, the long-run and short-run relationships, respectively, are estimated using the following selected ARDL models:

$$Linf_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} Linf_{t-i} + \sum_{i=0}^{n} \alpha_{2i} Lun_{t-i} + \sum_{i=0}^{n} \alpha_{3i} LM2_{t-i} + \sum_{i=0}^{n} \alpha_{4i} LRER_{t-i}$$
$$+ \mu_t$$

(2)

$$\Delta Linf_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} Linf_{t-i} + \sum_{i=0}^{n} \alpha_{2i} Lun_{t-i} + \sum_{i=0}^{n} \alpha_{3i} LM2_{t-i} + \sum_{i=0}^{n} \alpha_{4i} LRER_{t-i}$$
$$+ \psi ECM_{t-1} + \xi_t$$

(3)

Where

The coefficients in the short-run equation are related to the dynamics of the model's convergence to equilibrium in the short-run and ECM_{t-1} is the lagged error correction term which shows how quickly the short-run equation converge to the long-run equilibrium.

It should be stated that since the level of inflation had very high variability, its logarithm is used as a variable. In other words, using the natural logarithm seemed logical in order to control the impassionate behavior of the inflation. It is a common and also a robust way when you face such high inflation rates over a long period. And also, there are many practical studies, which used such a method (see, e. g., Aisen and Veiga (2006) and Shahbaz et al. (2016)). Although there are no negative observations for logarithm in this model, Aisen and Veiga (2006) believe that the advantages of using log inflation overcome the disadvantage of losing some otherwise usable observations.

The government in Iran uses money creation as a way of paying its spending. In other words, according to the structure of Iran's economy the variable, liquidity, has an important message: besides explaining the directions of the monetary policies explicitly, it would implicitly showing the fiscal conditions of the government. Regarding the double-digit inflation since 1973, the economic conditions of Iran lead people to hold foreign money as an asset. On the other hand, based on the national reports (Iran Customs Administration) most of the import includes capital and intermediate goods. Hence, it is not unreasonable to assume the real effective exchange rate as an effective factor on inflation.

2.1.2. Artificial neural network (ANN)

Artificial neural network model's successes in economics (see, e. g., Kuan and White, 1994) have led us to apply it as an estimation method.

The neural networks' structure is as follows: A neural network consists of many neurons grouped in numbers of layers that the main layers are: (1) input layers (2) hidden layers (3) output layers. The numbers of sub-layers have no special rule and are determined by the problem complexity. In general, a neural network is a set of connected input and output units that each connection has an associated weight (Thawornwong and Enke, 2004).

Input layers include some neurons equal to the explanatory variables' number that in the related literature, they are known as input variables. Accordingly, every artificial neuron receives some inputs, and this process leads them to produce an output. Hidden and output layers consist of information processing units (neurons). In these units, the algebraic operation is performed on the input data, and the result is sent as a new input to the other neurons in the subsequent layers. Neurons in the hidden layers play a fruitful role in this process that its operations in the literature, are called training process. During the disparate inputs training, the values are changed dynamically until their values become balanced; therefore, each input will lead to a favorable output. The units
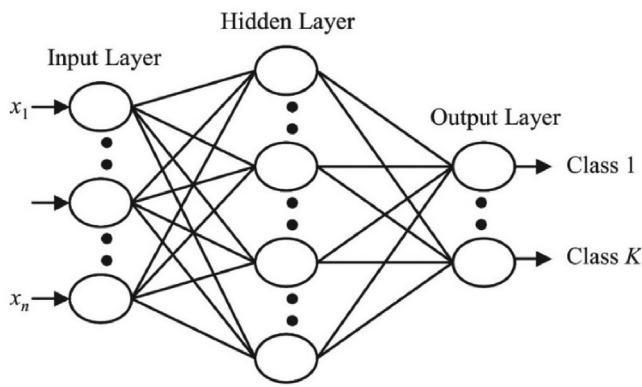
Fig. 1. A three-layer feed-forward neural network used for classification. Adopted from Thawornwong and Enke (2004).

of output layers act as the same as the explained variables in the regression that in the literature, they give target data. These estimated data are the outputs (see Fig. 1).

Different measures are applied to examine the estimation accuracy and forecasting ability of different estimators. The most popular ones are Mean Squared Error (MSE) or Root Mean Squared Error (RMSE) and Median Absolute Deviation (MAD).

To evaluate the performance of the chosen methods, these three measures are applied in order to compare and conduct performance evaluation.

2.2. Empirical results

In Phillips Curve modeling, the proposed model can be efficaciously estimated by the ARDL regressions and ANN.

It should be noted that all data include 49 annual data over 1968–2016, and they were extracted from the World Bank's database except unemployment, which was extracted from the Management and Planning Organization of Iran (MPO).

2.2.1. Econometrics methods

2.2.1.1. Stationarity. Even though the ARDL framework does not require pre-testing variables to be done due to the bounds test for cointegration, it is important to conduct the stationarity tests in order to ensure that the variables are not integrated of order 2 [I(2)]. Note that some details of the unit root tests such as the critical values and the case, no intercept no trend, are not discussed here because of conserving space. The details of the stationarity tests on series based on the Augmented Dickey-Fuller (ADF), and Phillips–Perron (PP) tests are available from the authors upon request. So we just provide a brief result of what has obtained from the unit root tests.

The results in Table 1 show that there is a mixture of I(0) and I(1) of variables and therefore, the ARDL procedure could be proceeded with.

2.2.1.2. Autoregressive distributed lag (ARDL). In this section, first, the long-run relationship among the variables is examined using the ARDL

Table 2
Bounds F-test for cointegration.

Dependent Variable	F-test statistic (SBC ARDL)
Linf	(15.456)*** (1, 2, 2, 1)[1]
asymptotic critical values[2]	

	I(0)	I(1)
1%	4.29	5.61
5%	3.23	4.35
10%	2.72	3.77

*** denotes statistical significance at 1%. (1) The optimal lag in the parentheses using SBC. (2) asymptotic critical value bounds are obtained from Narayan (2005).

Table 3
Estimated autoregressive distributed lag models, long-run coefficients, and short-run error correction model.

dependent variable: Linf, ARDL(1,2,2,1)			
Regressor	Coefficient	Standard error	p-value
Panel A. Estimated long-run coefficients			
Lun	1.980566	0.770114	0.0143
LM2	−0.132099	0.162329	0.421
LRER	0.078478	0.120862	0.5201
Panel B. Error correction representation for the selected ARDL			
Intercept	0.051681	0.235879	0.8278
D(Lun)	1.282501	0.602766	0.0401
D(Lun(-1))	−1.852361	0.612244	0.0045
D(LM2)	1.378581	0.688268	0.0525
D(LM2(-1))	1.87524	0.69268	0.0102
D(LRER)	1.667088	0.262334	0
ECM(-1)	−0.750674	0.091819	0
$\bar{R}^2$	0.65		
F-statistic	15.27		
RSS	4.04		
DW-statistic	1.94		

Note for Panel B: RSS stands for Residual Sum of Squares.

Table 4
Parameters of the effectualness of the estimators.

	MSE	RMSE	MAD
ARDL	29.12799591	5.397035845	3.790841723
ANN	14.20556177	3.769026635	2.213916359

bounds testing procedure of cointegration (see Table 2). Secondly, short-run and long-run equations will be presented in Table 3.

An appropriate lag selection in the ARDL model is based on a criterion such as Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC) and Hannan-Quinn (HQ). As the SBC tends to define more parsimonious specifications, is generally used in preference to other criteria (Pesaran and Shin (1998)). In this study, regarding the sample size, the SBC is used to select optimal lag for the ARDL model.

According to SBC, the optimal lag for this study is 2. Since Linf is the dependent variable and its F-statistic, which turns out to be 15.456, is higher than the upper bound critical value of 5.61 at the 1% level of significance, then the null hypothesis of no cointegration among the variables in Eq. (1) is rejected. So, there is a long-run relationship

Table 1
Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root tests.

Series	Intercept		Trend and Intercept		order of integration
	ADF	PP	ADF	PP	
Linf	(−3.444)**	(−5.441)***	−3.155	(−4.731)***	I(0)
Lun	(−6.864)***	(−6.868)***	(−6.839)***	(−6.842)***	I(1)
LM2	(−5.042)***	(−5.057)***	(−4.987)***	(−5.005)***	I(1)
LRER	(−3.904)***	(−3.364)**	(−3.844)**	(−3.330)*	I(1)

*, ** and *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 5
Forecasted value of inflation under the scenarios.

	2017	2018	2019	2020	2021	2022	2023	2024	2025
Scenario 1	10.3215	12.5425	14.7726	17.3397	21.5213	24.3269	26.8514	29.5692	33.5419
Scenario 2	10.3215	12.5425	13.7726	16.3397	19.5213	22.3269	25.8514	27.5692	32.5419
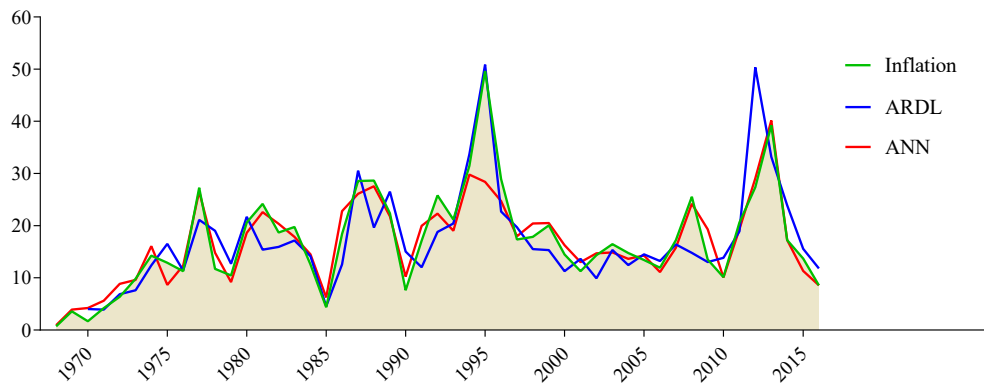
Fig. 2. Actual Iran inflation rates and fitted values during the period of 1968–2016 by employing ARDL and ANN.
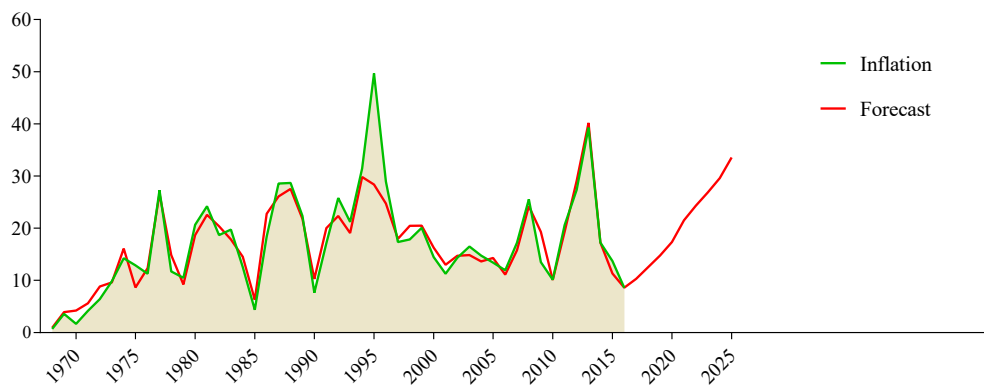

Fig. 3. Actual Iran inflation rates and forecasted values under the first scenario.
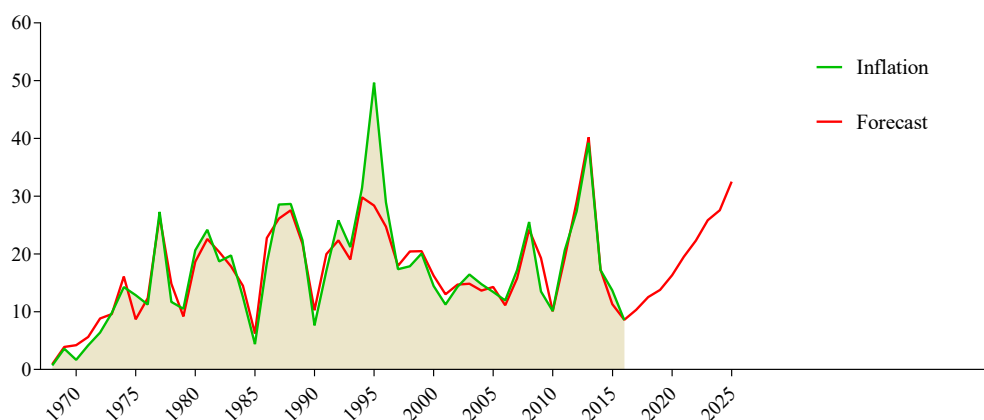

Fig. 4. Actual Iran inflation rates and forecasted values under the second scenario.

amongst the variables.

A number of diagnostic tests to the ECM were applied and no evidence of serial correlation and heteroskedasticity effect in the disturbances were found.

2.2.2. Artificial neural network (ANN)

To design an ANN model, two neurons were considered for the input layer. What was used in the competing ARDL model presented in the previous section were exactly the same as variables, which were choose for the input layers. This will supply a balanced playing field for the comparison.

The second step is the sample size determination for the learning and the test section. For this purpose, the sample size was divided into two parts: the period of 1968–2005 was considered for the model learning

and validation. The period of 2005–2016 was used for the test. Finally, the neurons number in the output and intermediate layers were determined. In this research, the neurons number in the output layer in this research was taken into account by considering that the target variable is inflation. The neurons number in the intermediate layer was determined by the error test method. In this way, for this model, ten neurons were embedded in the middle layer.

In the next step, a series of parameters and internal elements of the model such as learning coefficient, iterations number, the amount of expected prediction error, as well as, the activation functions type in the middle and output layers were determined. In this regard, the sigmoid tangent function for the middle layer and the linear function for the output layer were considered. After all these steps, the artificial neural network learning principle was determined, which in this study the LM[1] algorithm was adopted in order to make the training process fast.

2.2.3. Method comparison

The obtained values of MSE, RMSE and MAD for both methods are presented in Table 4.

As it is shown in Table 4, the designed neural network is more accurate in forecasting inflation than the ARDL method.

Fig. 2 plots the original inflation observations and the fitted inflation values by utilizing ARDL and ANN methods. The fitted values estimated by ANN are very close to the actual inflation observations.

2.2.4. Forecasting strategy

Based on these results and the performance of the ANN in forecasting inflation, this approach was chosen for out-of-sample prediction. In this case, two scenarios were applied to the designed ANN to forecast Iran's inflation up to 2025.

Scenario 1: 4%, 15.5% and 8% annual increase in the unemployment, liquidity and real effective exchange rate respectively.

Scenario 2: 4%, 30.4% and 15.6% annual increase in the unemployment, liquidity and real effective exchange rate respectively.

The first scenario is chosen regarding the past trend of the variables, liquidity and real effective exchange rate, in the whole period. And, the second one is chosen according to the present conditions. The unemployment growth in both scenarios is according to the current terms of Iran's economy. This will provide a level playing field for checking the monetary authority impacts on the structure of Iran's economy with high economic interventionism by the government.

3. Conclusions

In this paper, ARDL regressions and ANN approaches were employed in order to investigate the so-called Phillips curve. Two approaches of acquiring the Phillips curve in the ARDL and ANN skeletons were compared with each other, and then the ANN is proposed. According to both Table 3 and Fig. 2, empirical results of Iran's data exhibit that the ANN method accuracy was more precise than the ARDL method. Regarding the results of both approaches, the inflation rate is influenced by unemployment, liquidity and real effective exchange rate in the short-run. The point is that in the short-run all variables influence is positive except lag of first-difference of unemployment, which means that a given small change in the interested variables causes progressive changes in inflation but the effect of the changes in the unemployment will emerge in both current and the next period. According to the long-run coefficients it should be stated that the variables, liquidity and real effective exchange rate, do not influence the inflation behavior in the long-run. It is reasonable to implicitly express that the long-run results acknowledge the stagflation in Iran over the given period.

The scenarios' results by the approach of ANN suggests that inflation tends to increase by rising the considered variables. Two main

conclusions can be derived from these results. At first, this issue that a crucial monetary policy signal has emerged. The monetary authority should respond asymmetrically to different economic circumstances. If some inflationary pressure is expected in the future, then, the policy-makers should pay more attention to the inflation sensitivity more than anything else. Secondly, as the forecasted values were reported in Table 5 and shown in Figs. 3 and 4 under both scenarios in a level playing field, the monetary authorities also has an obvious booster rule.

The ANN success in such study suggests that it may apply as a practical instrument for economic analysis in various areas, such as the Phillips curve with more theoretical specifications complexity.

Declarations

Author contribution statement

Sayyed Abdolmajid Jalaee: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Mehrdad Lashkary: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Amin GhasemiNejad: Performed the experiments.

Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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