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A NEURAL NETWORK AND ECONOMETRIC COMPARISON OF THE RELATIVE IMPORTANCE OF FISCAL AND MONETARY ACTIONS

Mohamad Shaaf*

ABSTRACT

This study uses the neural network and econometric models to explore the importance of fiscal and monetary policy on GNP. The findings suggest that fiscal policy is more influential than monetary policy, and the neural network forecasts of GNP are more accurate and have less variation than those of the econometric approach.

I. Introduction

The relative influences of fiscal and monetary policy on the economy have for decades been studied intensively by economists of diverse persuasion and opposing ideologies. These studies used econometric models with different structures and variables, and have produced findings that are diverse, controversial, and still under dispute.

Two categories of econometric models have been used to measure the relative importance of fiscal and monetary policy. The first to be developed was the large-scale structural equation models of the Keynesian persuasion, which concluded that fiscal policy is more influential than monetary policy. Monetarist economists subsequently developed a first-difference reduced-form scheme (Andersen and Jordan, 1968) and, later, a growth version of the same reduced form (Carlson, 1980), called the St. Louis model. This model indicated that monetary policy had a greater impact than fiscal policy. In recent years a new econometric method called Vector Autoregressive (VAR) model has developed, and renewed the old debate into a new round of controversy (Todd, 1990).

The purpose of this study is to investigate the relative importance and the magnitudes of the influence of fiscal and monetary policy on

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*Professor of Economics, University of Central Oklahoma, Edmond, Oklahoma. Special thanks to Professor John Caldwell for reading the final draft of this paper and making editorial changes.

the economy, using a new approach called artificial neural networks. Neural networks are trained with some learning rule. Furthermore, in econometrics one must make many assumptions about the data, and must sometimes limit the analysis to a certain number of possible interactions. By contrast, neural networks are basically "nonparametric," and the data do not need to satisfy any assumptions. The St. Louis version of econometric model is also applied to the same data, and the results are compared with those of the neural networks. The findings of neural network approach and the St. Louis model suggest that the influence of fiscal policy is stronger than that of monetary policy. Moreover, the simulation of the forecast of GNP by the neural network method gave lower forecast errors and more stable forecasts than those of the St. Louis model.

A brief explanation of the neural network approach and the St. Louis model is in order. (Large scale structural and more recent Vector Autoregressive (VAR) models which are still controversial are beyond the scope of this study.) Following this explanation, the empirical findings of these two methods are presented.

II. Models of the Study

Neural Networks

The study of neural networks is a branch of the field of artificial intelligence. Like the structure of the brain, neural networks are multiple-layer configurations consisting of simple processing elements (called PE's) that interact with each other through weighted connection in the system. A typical neural network consists of: 1) an input layer, 2) one or more intermediate or hidden layers, and 3) one output layer. A general design of a network, with one output, two inputs, a bias, and a hidden layer, is used in this study as shown in Figure 1.

Each connection has a weight, and each element computes a weighted sum of the incoming values and passes this sum through a nonlinear or linear function as output. The role of the hidden layer(s) is a processor and a bridge between the inputs and output(s). The mathematical function of the hidden layers is in different forms.

In this study, a neural network consisting of two different mixtures of GNP as output and federal government expenditure (G), and the M1 money supply as inputs are used. The inputs and output are those which were used by different versions of the famous St. Louis Model (Andersen and Jordan, 1968; Carlson, 1980).

Notice that inputs of this network are not only connected indirectly through the hidden layer, but also connected directly to the output (see Figure 1). Furthermore, there is a bias processing element (PE) that is connected to the output. The bias PE is similar to the intercept concept in equations of econometric models, and it absorbs noises of other contributors to the output in the system. Neural networks, unlike econometric models which have to pass some degree of assumptions and therefore become parametric, are "non-parametric" in nature, even though the weights of connections are parameterized.

The three main phases in the operation of a network are Learning, Recall, and Testing. In the learning phase, the neural network recognizes a pattern between inputs and outputs and estimates the final output, called actual, A. Subsequently, this output is compared with the desired output, D, and errors are calculated. The errors become a factor to adjust the weights and subsequently to reduce the errors and readjust the weights of the connections. This process continues further until the errors decline to an acceptable level, if possible. Through this process the neural network learns the rules and adapting patterns for processing the knowledge. The resulting pattern of linking the inputs to the output(s) in the learning process can be used for testing the accuracy of the networks. In addition, the pattern can be used for prediction of the output(s), given the inputs.

The most widely used neural network model is back propagation, which is an algorithm for adjusting connection weights in a multiple layer network. Back propagation is a learning design by which the multi-layer network is set for pattern recognition utilizing actual cross section or time series data as the external teacher. It calculates the summation of multiplication of inputs by their corresponding weights as follows:

$$(1) \quad X_J^{[s]} = f\ (\sum_i\ (x_{ji}^{[s]} * W_{ji}^{[s-1]}) = f\ (I_J^{[s]}).$$

Where $X_J^{[s]}$ is the current output state of jth neuron in layer s, $W_{ji}^{[s-1]}$ is the weight on connection joining ith neuron in layer [s-1] to jth neuron in layer s, and $I_J^{[s]}$ is the weighted summation of inputs to jth neuron in layer s.

This weighted summation is then transformed by a transfer function to the hidden layer. Three common non-linear transfer functions used in artificial neural networks are the Sigmoid, hyperbolic tangent, and sine functions. The Sigmoid transfer function, which is used in this study, is a continuous monotonic mapping of the input into a value between zero and one. The Sigmoid function for the local error, e, is a smooth version of {0,1} step function, and is defined as

(2) $f(z) = (1 + e^{-z})^{-1}$.

The local error at processing element j in level s is determined by

(3) $e_j^{[s]} = dE / d(I_j^{[s]})$.

Here E is the global error function which is differentiable of all the connection weights in the network. Using the chain rule twice in succession gives a relationship between the local errors at a particular processing element at level s and at the level s +1 as

(4) $e_j^{[s]} = f'(I_j^{[s]}) * \Sigma(e_k^{[s+1]} * Wkj^{[s+1]})$.

Since from equation (1) $f'(z) = f(z) * (1.0 - f(z))$, equation (4) can be rewritten as

(5) $e_j^{[s]} = x_j^{[s]} * (1 - x_j^{[s]}) * \Sigma(e_j^{[s+1]}) *$

$W_{kj}^{[s+1]}$.

The summation term in (5) which is used to back-propagate errors is analogous to the one in (1) which is used to forward propagate the input through the network.

To increment or decrement the weights in order to decrease the global error a gradient descent rule is used as follows:

(6) $dW_{ji}^{[s]} = -\mathit{lcoef} * (dE / dW_{ji}^{[s]})$.

where *lcoef* is a learning coefficient, and the partial derivative in (6) is

(7) $(dE / dW_{ji}^{[s]}) = (dE / dI_j^{[s]}) *$

$(dI_j^{[s]}) / (dW_{ji}^{[s]})$

$= -e_j^{[s]} * x_i^{[s-1]}$

and combining (6) and (7) together gives

$$(8) \quad d\, W_{ji}^{[s]} = \mathit{lcoef} \; * \; -e_{j}^{[s]} \; * \; x_{i}^{[s-1]} .$$

Suppose the desired output, D, is specified by a teacher, and the actual output, A, is produced by the network with its current set of weights. Then the global error function, E, is the square of the Euclidean distance between the desired output and the actual output of the network for a particular input pattern, and is given by

$$(9) \quad E = 0.5 \; * \; (D_{k} - A_{k})^2$$

where $(D_{k} - A_{k})$ is the raw local error. From (3), the scaled "local error" at each processing element of the output layer is determined by

$$(10) \quad -e_{k}^{[0]} = - d\,E / d\,I_{k}^{[0]} = - (d\,E / d\,A_{k}) \, *$$

$$(d\,A_{k} / d\,I_{k}^{[0]}) = (D_{k} - A_{k}) \; * \; f'\,(I_{k}).$$

The sum of all pattern specific error functions is the overall global error function. The back-propagation algorithm modifies the weights to reduce the particular component of the overall error function.

One way to adjust the weights is by the Delta rule, which incorporates the learning coefficients, *lcoef*, and another parameter called momentum (M) as follows:

$$(11) \quad d\,W_{ji}^{[s]} = \mathit{lcoef} * e_{j}^{[s]} \; * \; x_{i}^{[s-1]} \; +$$

$$M * d\,W_{ji}.$$

The momentum (M) is a parameter which is used to smooth learning. Its function as a low-pass filter is to set an appropriate learning rate and convergence speed for the network.

The "explain" command reveals the information about the causes and the magnitudes of contributions of inputs on the output(s). This information is somewhat similar to the measure of elasticity of output for each input in the econometric approach.

Econometric Models

The structural form econometric models of the United States economy which are used for forecasts of the GNP and other macro measures are complicated with different sectors and large number of equations. The St. Louis models are of the much simpler reduced form variety. Their use has been the subject of frequent attack and they remain controversial.[1]

The first version of the model was introduced in 1968 by Andersen and Jordan in the form of first difference as follows:

$$(12)\quad \Delta Y_t = a + \sum_{i=0}^{4} b_i \,\Delta M_{t-i} + \sum_{i=0}^{4} c_i \,\Delta G_{t-i} + \sum_{i=0}^{4} d_i \,\Delta R_{t-i} + e_t,$$

Where Y= Nominal GNP
M= Money supply, M1
G= High-employment federal government expenditures
R= High-employment federal government revenues
e= error term.

The Δ's represent the first differences; for instance, $\Delta Y = Y_t - Y_{t-1}$, and $\Delta G = G_t - G_{t-1}$. The coefficients a, b, c, and d are the parameters of the model. Equation (12) as a reduced form model assumes that the current quarterly changes in output, ΔY, depend on the current quarterly changes in money supply, M1, and current quarterly changes in high-employment federal government expenditures, G, and the last four quarterly changes of these two policy variables. Note that the model also includes the current and last four quarterly changes in high-employment federal government revenues. Furthermore, the model assumes that the impact of these exogenous variables follows an Almon distributed lag (1965) of fourth degree polynomial, and that the impact is constrained with both endpoint parameters equal to zero.

In the later version of the model, the high-employment federal government revenue in equation (12), term R, was dropped (Andersen and Carlson, 1970), and presented as

$$(13)\quad \Delta Y_t = a + \sum_{i=0}^{4} b_i \ \Delta M_{t-i} + \sum_{i=0}^{4} c_i \ \Delta G_{t-i} + e_t,$$

Finally, the model was presented in the form of growth specification (Carlson, 1980) as follows:

$$(14)\quad \Gamma Y_t = a + \sum_{i=0}^{4} b_i \ \Gamma M_{t-i} + \sum_{i=0}^{4} \Gamma G_{t-i} + e_t,$$

where Γ represents the rate of growth of variables, and Y, M, and G represent GNP, money supply, and high-employment federal government expenditures respectively. According to this equation, the growth of GNP depends on the current, and four quarter lags of the growth of money supply and the current and four quarter lags of the growth of federal government expenditures. Again, the model assumes that the impact of these two variables follows an Almon type distributed lag of fourth degree polynomial, and that the impact is constrained with both endpoint parameters to equal zero.

In this study, and for the purpose of comparison with the results of the neural network, the growth versions of St. Louis model--equation (14)--was used. In the next section, the results are presented and compared.

III. Empirical Results

Neural Network Method

The back propagation technique, a Delta-learning rule, and a Sigmoid transfer function were considered appropriate for the learning and pattern recognition.[2] Quarterly data from 1970-1 to 1992-1 for GNP as output, and for money supply and government expenditure as inputs, were used. Two categories of data for government expenditures were utilized: the high-employment government expenditure (H), and the actual government expenditure (A).

The combinations of data for different variables resulted in two mixtures as follows:

1)HG: The rate of growth of: GNP as output, high employment government expenditures and M1 money supply as inputs.

2)AG: The rate of growth of: GNP as output, actual government expenditures and M1 money supply as inputs.

Table 1 presents the results of the learning of the neural network for each of these two mixtures. The input value column represents results of the current output (GNP) value of the PE where the connection originates. The estimated weights of the connection between the inputs PE and the output (GNP) are also shown in the table. In this study, variable weight (V) with relative scope connection (r) are used. The Delta weight is the result of the last change in the connection weight.

These findings suggest that the signs of the weight of both the high employment and actual government expenditures (G), and money supply are positive for both mixtures. Therefore, as expected, both government expenditures (high-employment and actual) and the money supply have positive influence on nominal GNP.

Furthermore, the weights of both government expenditures are higher than those of the money supply in both categories of data. Thus, according to the results of the neural network approach, the impact of government expenditures on GNP is stronger than that of money supply.

The neural network also calculated the relative sensitivity of GNP for each policy variable for the same data, and mixtures. Table 2 shows the averages and the standard deviations of the percentage changes of GNP as a result of a five percent change (dithering) in each of two exogenous variables (government expenditures and money supply). This concept is not exactly the same, but similar, to the elasticity measure in economics. Accordingly, for the mixture of the high-employment government expenditure and money supply, the coefficient of G is higher than that of M. Similar results are shown for the actual government expenditure mix. Thus, the sensitivity of GNP to government expenditures (multiplier) is stronger than that of monetary policy.

In the last column of Table 2, the differences between the coefficients of G and M are presented. According to these findings, the degree of responsiveness of GNP to fiscal policy is stronger than that of monetary policy.

Table 2 also presents the variations of the coefficients of GNP due to the changes in those exogenous variables, measured by their average standard deviations. The low standard deviations of all these variables suggest that the estimated coefficients for these two policy variables are very concentrated and do not have large variations. Indeed, some of these standard deviation numbers are very close to zero.

Econometric Method

To compare the results of the neural networks with those of the traditional econometric approach, the growth version of the St. Louis model (equation [14]) was used. Again, quarterly data from 1970-1 to 1992-1 only for the mixtures of the high employment government expenditure were applied to estimate the parameters of the equation. These findings are shown in Table 3.

In this table G represents the rate of growth. Accordingly, the sum of the coefficients of the distributed lags of fiscal policy of 0.37334 is slightly higher than that of monetary policy of 0.27863. Furthermore, although the last lag of the money supply is negative, its magnitude is close to zero. In addition, the 't' ratio of the sum of the coefficients for G is higher than that of M. Thus, the findings of the growth version of the model suggest that fiscal policy is more effective than monetary policy.[3]

IV. Simulation and Comparison

To test the accuracy and validity of neural network forecasts, compared to those of the econometric method, total data of 85 observation (1970-1 to 1992-1) was divided into two parts. The first part (43 observations) was used for the learning of the neural network, and the estimation of the parameters of the econometric model. The second part of the data (42 observations) was used to forecast (simulate), test, and compare the performance of these two methods. Using the parameters of the neural network's learning run and the inputs of the second part, the output of the second part was forecast and compared with the desired data. Similarly, using the parameters of the econometric equations and the inputs of the second part data, the output of the second series was estimated and compared with the desired data. Then, the errors of the forecasts by both methods were calculated and they are shown in Figure 2.

As Figure 2 shows the forecast errors of neural network are smaller and, thus, more accurate than those of the econometric model. In addition, the mean square error and standard deviations of the errors for both the neural network and the econometric model were calculated and are shown in Table 4. The mean square error of the forecast errors from the neural network approach are, surprisingly, smaller than those of the econometric method. Also, the standard deviations of the error are smaller for the neural network forecasts than those of the econometric method. Thus, results of the simulation of the models suggests that the neural network forecasts are more accurate than those of the St. Louis version of the econometric approach.

V. Summary and Conclusions

The relative importance and the degree of effectiveness of fiscal and monetary policies have been investigated and debated for decades. These studies have used different econometric models and their results have been diverse and controversial. This study employed the neural network method as a new approach to answer this question and to compare its results with the St. Louis version of econometric approach. Quarterly data from 1970-1 to 1992-1 are utilized for both applications. The results of the neural network approach and St. Louis model suggest that fiscal policy is more effective and more important than monetary policy.

The results of the simulation of the neural network and the St. Louis model for the sample period strongly suggest that the former method gives more accurate, and more stable forecasts than the latter.

ENDNOTES

1. Immediately after the publication of the Andersen-Jordan model in 1968, the model was attacked on several grounds. First, it was argued that reduced form models are not valid econometrically. Second, the model was criticized on the ground of misspecification, in that important variables (such as investment, consumption, and exports) are omitted. Third, critics argued that the policy variables are not strictly exogenous. Finally, critics attacked the model's conclusions that monetary policy is more powerful than fiscal policy, and that the latter has no lasting effect on nominal GNP. Since that publication, both sides of the debate have grown to believe that the role and the importance of other non-policy variables are even greater than those of the policy variables. These were called "Z -factors," and their relative magnitude has been estimated and recognized before.

2. For more detail about artificial neural network, and its comparison with the econometric method see NeuralWare, Inc.(1991).

3. These findings are not consistent with those of the early versions of the St. Louis model and those of the more recent studies by authors like Batten and Thornton (1986), Carlson (1986), and others. The inconsistency is mainly due to the use of different sample periods, as was acknowledged by Jordan (1986). In that article, he cited three factors contributing to the so-called "failure" of monetarism. They are: (1) institutional changes, such as the Monetary Control Act of 1980, (2) the role of lags in the effectiveness of policies, and (3) the appropriate numerator in the measurement of velocity (income or transactions).

TABLE 1

RESULTS OF THE NEURAL NETWORK APPROACH TO THE IMPACT OF FISCAL AND MONETARY POLICY ON GNP

MIX	Input PE	Input Value	Weight	Delta Weight
HG*	Bias	+1.0000	-0.5125	+0.0001
	ΓG	+0.7216	+0.4044	-0.0001
	ΓM	+0.2477	+0.2407	+0.0002
	HIDDEN	+0.4776	-0.2487	+0.0001
AG	Bias	+1.0000	-0.4827	+0.0013
	ΓG	+1.0000	+0.3141	+0.0012
	ΓM	+0.6525	+0.2538	+0.0008
	HIDDEN	+0.4565	-0.2310	+0.0006

*HG: The rate of growth of: GNP as output, high employment government expenditures and M1 money supply as inputs.

AG: The rate of growth of: GNP as output, actual government expenditures and M1 money supply as inputs.

TABLE 2

NEURAL NETWORK'S AVERAGE AND
STANDARD DEVIATION OF GNP ELASTICITY
TO GOVERNMENT EXPENDITURES AND MONEY SUPPLY

MIXTURE		Government Expenditures (G)	Money Supply (M)	(G-M)
HG*				
	Average	10.120	6.12	4.0003
	Stand Devn	0.0038	0.002	
AG				
	Average	7.8546	6.4261	1.4284
	Stand Devn	0.0024	0.0019	

*HG: The rate of growth of: GNP as output, high employment government expenditures and M1 money supply as inputs.

AG: The rate of growth of: GNP as output, actual government expenditures and M1 money supply as inputs.

Stand Devn = Standard Deviations

TABLE 3

RESULTS OF THE
GROWTH VERSION OF ST. LOUIS MODEL WITH
GOVERNMENT EXPENDITURES AND MONEY SUPPLY

Variables	Coefficient	T-Statistics
Constant*	0.7567	1.5833
ΓG0	0.096	1.8080
ΓG1	0.0832	1.8731
ΓG2	0.0597	1.2646
ΓG3	0.0632	1.3981
ΓG4	0.0711	1.3123
SUM	0.3733	2.8124
ΓM0	0.0730	0.6575
ΓM1	0.1200	1.8576
ΓM2	0.1014	1.0741
ΓM3	0.0272	0.4107
ΓM4	-0.0430	-0.3865
SUM	0.2786	0.5764
R2	0.1430	
Adjusted R2	0.0736	
DW	1.3994	
SE	1.0505	
F(6,74)	2.0586	
No of Observations	81	

*Γ is the rate of growth

TABLE 4

MEAN SQUARE, AND
STANDARD DEVIATION OF THE FORECAST
ERROR BY NEURAL NETWORK AND ECONOMETRIC MODELS

Measures	NEURAL NETWORK MODEL	ECONOMETRIC MODEL
MSE*	%10.0	%13.7
STAND DEV	%1.27	% 2.0

*MSE = Mean Square Error, STAND DEV = Standard Deviation.

FIGURE 1

A Neural Network with One Input Layer (M and G),
One Hidden Layer, One Bias, and One Output Layer (GNP)

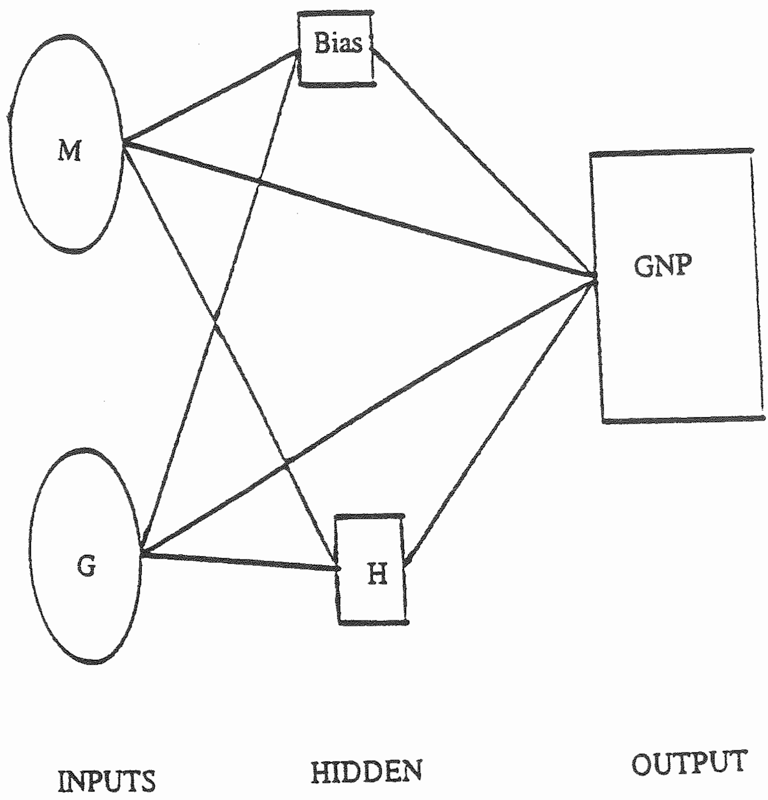
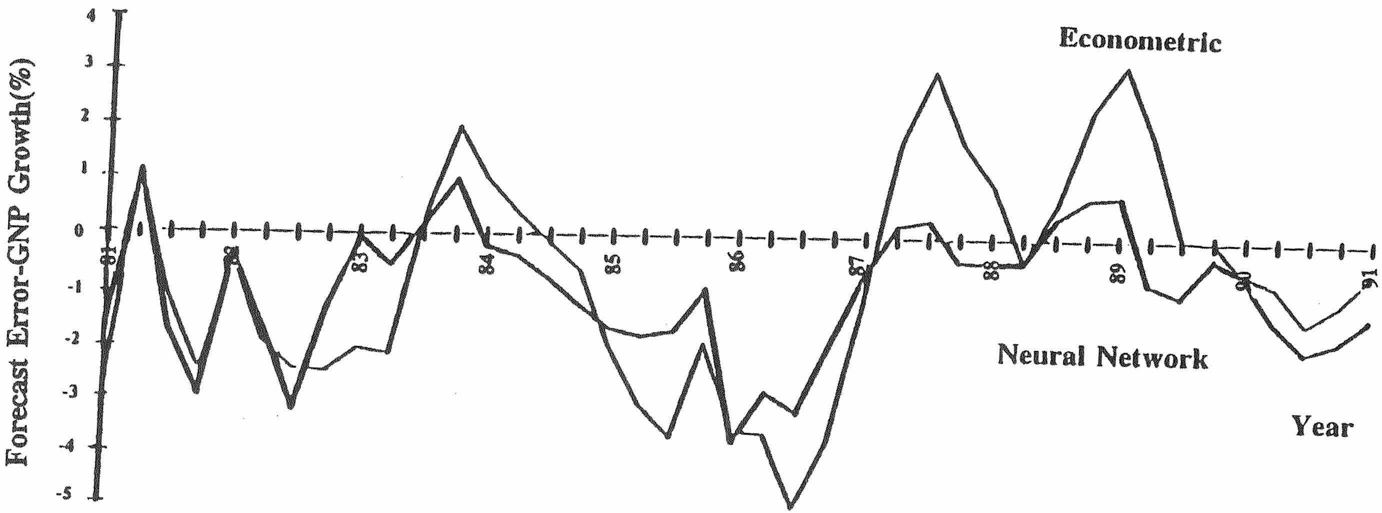


FIGURE 2

Comparison of Forecast Errors: Growth Version of Neural Network and Econometric Models



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