Professor Hamid ABRISHAMI
Faculty of Economics, University of Tehran
E-mail: abrishami_hamid@yahoo.com
Mohsen MOHAGHEGH, MA Student
Faculty of Economics, University of Tehran
E-mail: mmohaghegh@ut.ac.ir
Mahdi NOURI[1], PhD Student
Faculty of Economics, University of Tehran
E-mail: mahdinouri@ut.ac.ir

INFLATION- GROWTH NEXUS IN IRAN: INTRODUCING AND APPLYING THE GMDH CAUSALITY TEST

Abstract. *The relationship between economic growth and inflation is one of macroeconomic topics which despite several empirical and theoretical studies, still remains controversial. Considering the nonlinear essence of this relationship which most current studies verify, this paper on the basis of GMDH neural networks and underlying notion of Granger causality test proposes a new causality test for identifying the cause and effect in inflation-growth nexus. As an empirical application, this test is used to study the inflation-growth nexus in Islamic Republic of Iran. Our test identifies change in price level as a nonlinear GMDH cause of economic output which is in line with our theoretical expectations. But in the opposite direction, we cannot conclude that economic growth is a nonlinear GMDH cause of inflation which highlights the role of other variables - possibly monetary ones.*

Keywords: *Economic Growth, Inflation, Causality, GMDH Neural Networks.*

JEL Classification: O40, E31, C45

Introduction

Low inflation rates as well as high economic growth are two important goals of all macroeconomic policies. This fact makes clarifying the relationship between these two variables so important. Addressing this issue is a coin. One side of this coin answers this question: is there any causal relationship between inflation and growth? And, if any, what we can conclude about the cause or effect, and the magnitude of it. But the

[1] - Corresponding author

other answers another question: through which mechanisms inflation and growth affect each other? Considering their critical policy implications, both questions have received great attention in either theoretical or empirical researches. In this paper we will introduce a practical method to answer first question.

The causal relationship between inflation and growth in both directions has been subject of several researches. Since 1970s, large body of studies focused on the unpleasant impacts of high inflation rates on economic growth (e.g. De Gregorio, 1992; Fisher, 1993 and Bruno & Easterly, 1998). The opposite causality direction (i.e. from growth to inflation) is also granted considerable attention (e.g. Barro, 1995, 1997; Guerrero, 2006; and Hwang 2007). With respect to policy implication, the result of our causality study is of great importance because can prove either effectiveness or neutrality of money in the one direction and applicability of supply side policies in the other. Reviewing the related works demonstrates that the majority of empirical studies, to test bilateral causal relationship between inflation and growth have used standard Granger causality Test.

This widely used test, in spite of great strengths, like any other method, suffers from some shortcomings including two main problems of linearity and stationarity assumptions. To obviate these shortcomings different amendments have been proposed. For example, since the relationship between inflation and growth is not necessarily linear, nonlinear causality tests are introduced and applied (e.g. Thirlwall & Barton, 1971; Gylfason, 1991; and Sarel, 1996). Contributing this strand of literature, in this paper we propose a new test and apply it in an empirical application. The underlying idea of Granger test is examining whether or not one variable can explain the variation of another variable significantly. Applying this idea, we will introduce a nonlinear non-parametric causality test which is based on a special category of Neural Networks proposed by Ivakhnenko (1968), Group Method of Data Handling (GMDH).

Iran as a developing large energy – mostly oil and gas – exporting country unfortunately still suffers high rates of inflation. The double digit yearly average rate of inflation in past two decades proves this claim. So, identifying the possible impacts of price stabilizing policies on economic growth is of great importance for Iranian policy makers. As an empirical application of our test, we use it to study the causal relationship between inflation and growth in Iran. The quarterly time series data of –logarithm of- Consumer Price Index (CPI) and Gross Domestic Product (GDP) from 1988 to 2008 are used in this paper.

The remainder of the paper is organized as follows: In section 2, based on previous studies, inflation-growth nexus and its nonlinear nature are briefly reviewed. In section 3 GMDH neural networks will be introduced. Section 4 proposes our causality test and compares it with traditional standard Granger causality test. In section 5 we will report our empirical results and finally section 6 concludes.

Inflation-growth nexus

Historically, it was widely believed that inflation is destructive for economy; however, in the 1960s the story was totally different. As Bruno and Easterly (1998) say, that “high-growth, low-inflation” period was “the Golden Age of the Phillips Curve in which inflation and growth were positively related in the short run”. Even for the long run, so-called structuralists suggested some theoretical explanations for positive or at least, no significant relationship between inflation and growth. They believed that since price stability which is obtainable through fiscal and monetary policy leads to higher unemployment and reduces growth rate, price instability -i.e. inflation- actuates economic growth. Tobin (1965) believes that inflation rate positively affects the rate of capital accumulation which implies a positive impact on economic growth. Structuralists argued that money and fixed capital are substitutes, so any increase in the rate of inflation leads to an increase in capital accumulation by shifting portfolio from money to capital (De Gregorio, 1992). Following this dominant point of view, several researches in that period suggested a positive -or no significant- relationship between output growth and inflation[1]. For example, Sidrauski’s growth model (1967) considers money –beyond neutral- superneutral. Lucas (1973) also suggests that low inflation rates by making prices and wages more flexible increase growth rate.

In the 1970s and 1980s, facts observed in real economies contradicted this view. In this period, many countries, specifically in Latin America experienced high rates of inflation. Empirical researches aimed to analyze the effects of these severe inflations on growth rates, though in some cases reported a transient positive interaction, mostly found negative relationship between inflation and growth (e.g. Kiguel & Liviatan, 1988; Dornbusch et al, 1990).

To combine theoretical and empirical explanations of both positive and negative relationship between inflation and growth, nonlinear specifications suggested in which inflation, below a critical rate, motivates growth –positive interaction- but when it goes beyond the threshold becomes destructive –negative interaction. This point of view is a special kind of reconciliation[2] between the two previous explanations; because suggests that the dominant idea about positive relationship between inflation and growth in 1960s occurred due to lack of enough empirical evidences of hyperinflation -beyond the threshold. Fischer (1993) firstly introduced the possibility of such relation which later followed by several others. Identifying the threshold level in which the sign of interaction changes is the Achill Hill of this body of research. Different empirical studies estimated various rates of inflation as the turning point in different countries (see Sarel, 1996; Ghosh & Phillips, 1998; Christoffersen & Doyle, 1998; and

1. Li (2006) and Bruno & Easterly (1998) surveyed some.

2. Another useful approach is classifying the results into two different time spans; positive relation in short-run and negative relation in long-run.

Khan & Senhadji, 2001, among others). Numerous studies have pursued this nonlinear approach but some researchers, going beyond, fitted splines. Of course it should be noted that "attempts at spline regressions are extremely sensitive to the one or two points in the relevant intermediate ranges, as Levine and Zervos (1993) show" (Bruno & Easterly, 1998).

Moreover, the more stylized facts confirmed a negative relationship, the more efforts economists made to identify channels through which inflation hinders economic growth. Many researchers have described different mechanisms to explain how inflation rate disorders the performance of financial system and becomes a major obstacle against economic growth. One of the most important explanations is that inflation reduces real returns to savings and causes an informational friction afflicting the financial system. This friction leads investors not to invest and thus credit rationing which reduces the capital available for investment. Meanwhile the efficiency of invested capital reduces too. These two impacts adversely affect the economic growth (Lucas, 1980; Lucas & Stokey, 1987; Choi et al, 1996; Azariadas & Smith, 1996). Moreover, Barro (1995) highlighted the role of reduction in the propensity to investment as a channel by which inflation decreases growth is.

On the other hand, some studies have focused on inflation uncertainty as an important factor in the relationship between inflation and growth. Friedman in his Nobel lecture (1976) argued that when inflation rate increases, the uncertainty about inflation rate increases too which leads to economic inefficiency and a lower output. According to him, higher inflation uncertainty disables the price mechanism; then resources allocate inefficiently; then economic output decreases. In particular, high inflation uncertainties not only make relative prices vaguer for consumers but also make entering into long-term contracts more difficult for risk-averse employers and employees. On the other hand, one may anticipate a positive interaction between output growth and inflation uncertainty by claiming that higher growth rates are accompanied with more inflation (the short-run Phillips Curve) and more inflation leads to more uncertainty about inflation (Jansen, 1989; Fountas & Karanasos, 2007).

Finally, some argue that the government strategies for financing large deficits are the best explanation of the negative relationship between inflation and growth. They believe that the decisions government made to regulate financial system are the cause of this negative impact. In other words, "the negative effect of inflation on growth is spurious as both high inflation and low economic growth are caused by policies of financial repression" (Andrés et al., 2004). Chari et al. (1996), also, comparing several quantitative models conclude that inflation does not affect economic growth significantly, but financial policies and their interaction with inflation have substantial effects on growth.

GMDH Neural Networks

Neural networks are highly flexible, semi-parametric data-based models. These models have been applied in many scientific fields including biology, medicine, engineering and economics. For economists, neural networks represent an appealing alternative to standard regression techniques and are particularly useful for dealing with nonlinear relationships. Ivakhnenko (1968) introduced an optimized Heuristic algorithm which was based on the concept of pattern recognition, GMDH neural networks. In that sense, GMDH networks are a refinement of traditional methods of technical analysis and are appropriate for complicated higher-order regression systems.

By applying GMDH algorithm, a model can be represented as a set of neurons in which different pairs in each layer are connected through a quadratic polynomial and produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function $\hat{f}$ as an approximation of actual function f in order to predict output $\hat{y}$ for a given input vector $X = (x_1, x_2, x_3, \dots, x_n)$. Therefore, for M observations of multi-input-single-output data pairs:

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \qquad for\ i = 1, 2, \dots, M \tag{1}$$

We train a GMDH-type neural network to predict the output values $\hat{y}_i$:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) \qquad for\ i = 1, 2, \dots, M \tag{2}$$

Our goal is to minimize the prediction error:

$$Min \sum_{i=1}^{M} [\hat{y}_i - y_i]^2 = \sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) - y_i]^2 \tag{3}$$

General connection between input and output variables can be expressed by a complicated discrete form of the Volterra functional series which is known as the Kolmogorov-Gabor (Ivakhnenko,1971; Farlow, 1984; Nariman-Zadeh et al., 2002):

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} a_{ijk} x_i x_j x_k + \dots \quad for\ n = 1, 2, \dots, N \tag{4}$$

The full mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables (neurons), that is

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \quad for\ i = 1, 2, \dots, M,\ \ j = 1, 2, \dots, N \tag{5}$$

In this way, such partial quadratic description is recursively used in a network of connected neurons to build the general mathematical relation of input and output variables given in equation (4). The coefficients a_i in equation (5) are calculated using regression techniques (Farlow, 1984; Nariman-Zadeh et al., 2002) so that the difference between actual and forecasted values for each pair of input variables is minimized. Indeed, it can be seen that a tree of polynomials is constructed using the quadratic form given in equation (5) whose coefficients are obtained by least square method. In this way, the coefficients of each quadratic function G_i are obtained to optimally fit the output in the whole set of input-output data pairs.

In the basic GMDH algorithm, all the possibilities of two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of equation (5) that best fits the dependent observations ($y_i, i = 1, 2, \dots, M$) in a least square sense. Consequently, $\binom{n}{2}$ neurons will be built up in the first hidden layer of the feed forward network from the observations. In other words, it is now possible to construct M data triples $\{(y_i, x_{ip}, x_{iq}); (i = 1, 2, \dots, M)\}$ for $p, q \in \{1, 2, \dots, N\}$. In the matrix form of $Aa = Y$ where a is the vector of unknown coefficients of the quadratic polynomial in equation and $Y = (y_1, y_2, \dots, y_M)^T$ is the vector of output values from observation. Matrix A is made of input variables, their crossed values and their quadratics as stated in (5).

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations as follows:

$$a = (A^T A)^{-1} A^T Y \tag{6}$$

This determines the vector of the best coefficients of the quadratic equation (5) for the whole set of M data triples. It should be noted that this procedure is repeated for each neuron of the next hidden layer according to the connectivity topology of the network. However, such a solution directly from normal equations is rather susceptible to round off errors and, more importantly, to the singularity of these equations. Recently, genetic algorithms have been used in a feed forward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer (Nariman-Zadeh et al., 2002).

GMDH Causality Test

The concept of causality is “indispensible and fundamental” to all branches of science (Wold, 1954). This indispensible part has led to great discussions in various fields of science both philosophically and empirically. In econometrics, the concept of causality was firstly developed by Wiener and Granger (Wiener, 1956; Granger 1963, 1969) for examining the dynamic interactions between time series[1]. Since then, numerous researchers have frequently applied ‘Granger Causality Test’ in empirical studies.

The underlying notion of Granger causality between two time series examines if incorporating the information of one variable can improve our prediction of the other. Assume that $\{X_t\}$ and $\{Y_t\}$ are two stationary time series. Let I_T be the total information set available at time T. Besides, $\overline{X_T}$ contains all the values of X from

1. See Florens & Mouchart (1985) and Hoover (2008) for more details.

$t = 1$ to $t = T$. Let $\sigma^2(Y_t)$ be the variance of the prediction error of Y_t. Then X is the 'Granger Causal' to Y, if and only if $\sigma^2(Y_{T+1}|I_T) < \sigma^2(Y_{T+1}|I_T - \overline{X_T})$ (Kirchgässner & Wolters, 2007).

Alternatively, in a bivariate model, this test can be reformulated in a VAR specification:

$$\begin{cases} X_t = \varphi(L)X_t + \psi(L)Y_t + \varepsilon_t \\ Y_t = \varphi'(L)X_t + \psi'(L)Y_t + v_t \end{cases} \tag{7}$$

$\varphi(L)$,$\psi(L)$,$\varphi'(L)$ and $\psi'(L)$ are lag operators; ε_t and v_t are white noise error terms. In this often-used specification, Y is 'Granger Causal' to X when at least one of the estimated coefficients for the polynomial $\psi(L)$ is significantly different from zero. Similarly, X is 'Granger Causal' to Y when at least one of the estimated coefficients for the polynomial $\varphi'(L)$ is significantly non-zero.

The Granger causality test, like any other method, has both benefits and limitations. First of all, this test has assumed that all time series are stationary; the assumption which mostly violates in economic studies. Second, Granger test only examines linear relationship between included variables; the assumption which clearly does not necessarily cover all the causal relations in real world (Geweke, 1982). Third, According to Cheng & Lai (1997), if the selected Lag order is lower than real optimal lag, the some necessary explanatory variables will be omitted which leads to biased estimations. On the other hand, if the selected lag order is larger than real optimal lag, our estimations are not efficient.

To overcome with these shortcomings, different methods are suggested. For example, Granger (1986) claimed that non-stationarity of data does not threaten validity of the results if all variables are cointegrated. To obviate the linearity restriction, also, several generalizations have been suggested (see Baek & Brock, 1992 and Hiemstra & Jones, 1994, among others). Moreover, some tests applied smooth transition regression models to incorporate non-linearity (Skalin & Teräsvirta, 1999), some used local linear approximation of the nonlinear function (Chen et al., 2004) and some generalized Granger test on the basis of "a Taylor expansion of the nonlinear model around a given point in the sample space"(Péguin-Feissolle et al., 2008).

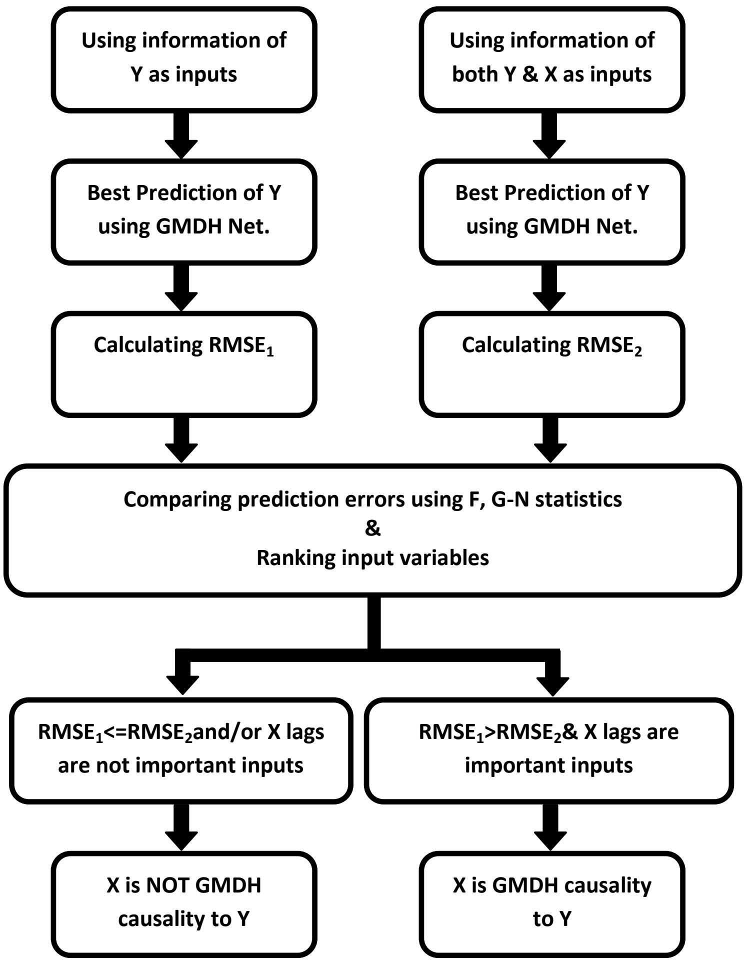

Figure 1: The procedure of GMDH causality test

As a part of this strand, this paper introduces[1] a causality test based on GMDH neural networks. Claiming that they may just improve our prediction without any explanation about the mechanism, some econometrists often criticize using Neural Networks in economic studies. This test suggests an operational method to extract policy-oriented information from neural networks.

1. Till now, we have found two similar ideas; an abstract by Xiang, W. Y. (2007) and some presentation slides by Chanzheng, H (2004). Our search for any paper relating to these works had no result.

In comparison with frequently used linear Granger causality test, this test is not dependent on the critical assumption of stationarity - or cointegration. In addition, the interactions between neurons in a network are nonlinear. So, this test captures nonlinear causal relationships. Moreover, on the contrary of Granger test, since our test is not based on the examining the null hypothesis of non-causality, the 'lag order problem' does not threaten the results. Nonlinear GMDH causality test is more flexible in adding new variables, so applying it, the 'identification problem' never occurs. Finally, this test is less affected by any structural change in the data. And finally, in this test we can rank the explanatory variables with respect to their contribution in improving our prediction; which can be used as method to compare the magnitude of relationship.

Fig. 1 depicts our proposed process for GMDH causality test. In this process, to examine the causality of the variable X to the variable Y, we will construct two GMDH neural networks. One of them uses the previous values of Y to predict future values of Y. But the second model, in addition to lag values of Y, incorporates lag values of X to make better predictions. Similar to Granger Causality Test, the notion is to test whether adding new information of X significantly improves our prediction of Y or not. Moreover, in best predictions of both networks, we can rank input variable with respect to their effectiveness in improving our prediction. If lag variables of X in the second network significantly decrease the Root Mean Square Error (RMSE) of prediction and if they remain among top important inputs of the network in our ranking, we can conclude that X is a "GMDH Causality" to Y.

Since neural networks are based on the information network extracts from the provided data, in most cases, adding new information (lag values of X) leads to better prediction. So, to make a reliable test, in the fourth stage, we examine how significant this improvement is and are new data effective or not? This goal is achieved by applying F and Granger-Newbold (G-N) statistics to compare RMSE1 and $RMSE_2$. In next section we apply this test to determine the causal relationship between CPI and GDP in Iran.

Empirical application

Data

First of all, it should be noted that since neural networks find out the data generating process by applying data mining and numerical techniques, using unelaborated data usually leads to better results. Then, we have used the data for CPI and GDP instead of inflation rate and economic growth rate and as proxies for them. The quarterly data for

CPI and GDP obtained from Central Bank of Iran's (CBI) reports. Our data covered the period of 1988 to 2008. Table 1 reports the summary statistics for the quarterly data of inflation rate, growth rate, CPI and GDP.

Table 1: Summary Stats.

	Inflation rate	CPI	Growth rate	GDP
Mean	0.044	159.200	0.013	78345.64
Maximum	0.177	542.087	0.130	125790
Minimum	-0.03	13.720	-0.061	42947
Std. deviation	0.03	142.503	0.037	21914.89
Skewness	0.872	0.980	0.363	0.567
Kurtosis	6.422	3.091	3.250	2.501
Jarque-Bera (P-value)	0.000	0.001	0.377	0.076

Causality Test

Inputs and run conditions play very important roles in neural networks. So, in the first step, to make best predictions, several try and errors performed. Based on them, we have used three lags of every input variable in our network. Besides, in all networks last 15 observations are used to evaluate the accuracy of prediction. Then, to examine the causal relationship from inflation to growth, we considered two networks; one used three lags of GDP to predict GDP (Net. 1) while the other used three lags of both GDP and CPI to forecast future output level (Net. 2). Similarly, to examine the causal relationship in the opposite direction, two other neural networks were applied; the first used three lags of CPI to predict future CPI (Net. 1) and the second used three lags of both GDP and CPI to forecast future price level (Net. 2). Our main goal is to test whether additional inputs incorporated in latter networks significantly improved our prediction of output or price level in comparison with the results obtained in initial networks.

To this aim, prediction errors are calculated. The results of calculating four main prediction error criteria - Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percent Error (MAPE) and Theil Inequality Coefficient (TIC)- are reported in Table 2. Of course in our causality test we usually use RMSEs.

Table 2: Prediction errors

		RMSE	MAE	MAPE	TIC
CPI to GDP					
	Net. 1	5719.751	3310.216	2.828835	0.025111
	Net. 2	2402.010	1973.118	1.718833	0.010452
GDP to CPI					
	Net. 1	14.54269	9.382377	2.416257	0.021301
	Net. 2	10.73904	6.660621	1.767806	0.015640

Moreover, Figures 2 & 3 show the realized and predicted values of dependant variables in out-of-sample periods (last 15 observations) in these four networks.

Incorporating new information of price level leads to better predictions of output. In other words, as seen in Fig. 2, predicted values of latter network (GDP2) tracks the fluctuations of real GDP (GDP) better than the predicted values of initial network (GDP1). Comparing the calculated values of prediction error criteria reported in Table. 2 approve this result. Besides, according to our neural network's output, all the additional lagged values of CPI considerably play important roles in making new generations of network in Net. 2; such that third lag of CPI is the most frequently used input. So, one may conclude that additional series are important inputs.

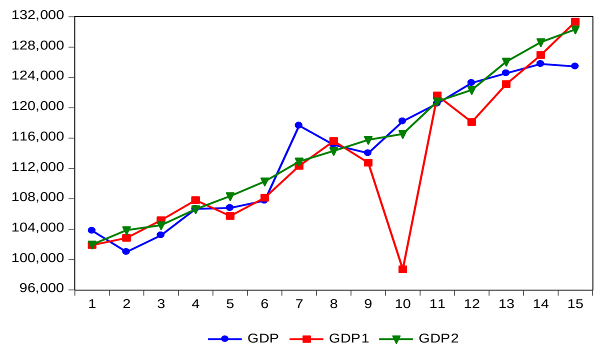

Figure 2: realized GDP (GDP), the prediction using previous GDP data (GDP1), the prediction using both GDP & CPI data (GDP2)

Similarly, Fig. 3 shows the realized values of price index (CPI), the predicted values of initial network which is based only on the lag values of CPI (CPI1) and the predicted values of the latter network which use both CPI and GDP data (CPI2). As seen, incorporating new information ends in better prediction. In other words, CPI2 tracks the line of realized values better than CPI1 specifically in last 5 observations. So, we may conclude that output level -if were- is a weak cause of price level. Of course, even after adding new information our prediction, especially in last two periods, are not so accurate; the fact suggests that, specifically in short run, other economic variables -possibly monetary ones- are the main causes of inflation. Besides, even after adding lagged series of GDP, first lag of CPI remains the most important input. Finally, Table 2 reports weak betterments in prediction error criteria.

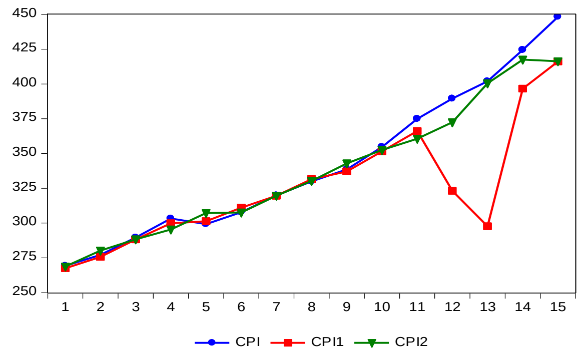

Figure 3: realized CPI (CPI), the prediction using previous CPI data (CPI1), the prediction using both CPI & GDP data (CPI2)

As expected, in predicting both series, adding new information has led to better predictions (i.e. all criteria reduced in second networks) but to make a valid conclusion, we should test the magnitude and statistical significance of these betterments. To this aim, we calculated F and Granger-Newbold (1977) statistics as follows:

$$F = \frac{RMSE_1}{RMSE_2} = \frac{\sqrt{\sum_{T+1}^{T+h} e_{1t}^2/h}}{\sqrt{\sum_{T+1}^{T+h} e_{2t}^2/h}} \tag{8}$$

$$G - N = \frac{r_{xz}}{\sqrt{(1-r_{xz}^2)/(h-1)}} \tag{9}$$

In (8) and (9), "h" is the number of predictions; $e_{1t} = \hat{y}_t^1 - y_t$ and $e_{2t} = \hat{y}_t^2 - y_t$ are the error series of the two predicted series. Besides, $r_{xz} = Ex_t z_t = E(e_{1t}^2 - e_{2t}^2)$ in which $x_t = e_{1t} + e_{2t}$ and $z_t = e_{1t} - e_{2t}$.

The results are summarized in Table 3.

Table 3: Comparing prediction errors

		Statistics	P-Value
CPI to GDP			
	F Stat.	5.670282***	0.00087
	G-N Stat.	4.602604***	0.00041
GDP to CPI			
	F stat.	1.833828	0.12582
	G-N Stat.	1.867504*	0.08291

*, **, *** show statistical significance in 10%, 5% and 1% level.

According to Table 3, both F and G-N tests approve that adding CPI information significantly improves our prediction from future GDP. Moreover, as stated above, CPI lags are important inputs. So, back to our definition, we can say that CPI is "nonlinear GMDH causality" for GDP. In the opposite direction the results are different. F test rejects and G-N test slightly accepts the hypothesis that GDP information significantly improves our prediction of CPI. So, although GDP lagged values are important inputs, we cannot argue that GDP is "nonlinear GMDH causality" for CPI. In other words, the hypothesis that economic growth is "GMDH causality" for Inflation is not approved.

Conclusion

To investigate the causal relationship between economic growth and inflation, we introduced a new nonlinear non-parametric causality test based on GMDH neural networks. Nonlinear GMDH causality test examines if adding new information of one variable to neural network's inputs significantly increases the prediction accuracy of other variable. This test, unlike to Granger test not only captures nonlinear relations but also is not dependent on stationarity of time series. Moreover, in this test lag order and identification problems do not occur. We applied this test to study inflation-growth nexus in Iran. Our results show that inflation is a "nonlinear GMDH cause" for growth which suggests that price stability policies have great gains. In the opposite direction, the causal impact of economic growth on inflation is insignificantly weak. So, we cannot conclude that growth is a "nonlinear GMDH cause" for inflation. This result indicates that in Iran, higher growth rates (supply side policies) do not necessarily stabilize prices. So, to analyze the causes of and control inflation, other policy variables are more important than factors actuate economic output.

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