Vol 4, Issue 4, Oct 2017
Journal of Health Management & Informatics
jhmi.sums.ac.ir
Original Article

Health impact on Economy by Artificial Neural Network and Dynamic Ordinary Least Squares

Marziyeh Sadat Safe[1], Mohsen Barouni[2*], Seyed Mojtaba Saif[3]

Received 20 Dec 2016 ; Accepted 10 May 2017

ABSTRACT

Introduction: Achievement of economic growth, as one of the most important macroeconomic variables, depends on the precise understanding of potential routes and the factors affecting on it. The aim of this study was to evaluate the health care sector's effect on Iran Gross Domestic Product (GDP), as the status of economy.

Method: Artificial Neural Network (ANN) and Dynamic Ordinary Least Squares (DOLS) were performed according to Iran GDP as the output variable and the input variables of life expectancy at birth, under five mortality rates, public health expenditures, the number of doctors and hospital beds during 1961-2012 in Iran. Data were collected from the Statistical Center of Iran, the Central Bank of the Islamic Republic of Iran, the World Health Organization and the World Bank databases. Data management and analysis were performed using Eviewes 7, stata 11 and also Mathlab. MSE, MAE and R^2 were calculated to assess and compare the models.

Results: One percent reduction in deaths of children under 5-years could improve Iran GDP as much as 1.9%. Additionally, one percent increment in the number of doctors, hospital beds or health expenditure would increase GDP by 0.37%, 0.27% and 0.29%, respectively. Mean Absolute Error (MAE) demonstrated the superiority of DOLS in the model estimation.

Conclusion: The lack of sufficient considerations and excellent models in the health care sector is the main reason for underestimating the effect of this sector on economy. This limitation leads to neglecting the resource allocation to the health care sector, as the great potential motivation of the economic growth.

Keywords: Neural Network, Health care sector, Life expectancy, Health expenditure, Econometric model

►*Please cite this paper as:*
Safe M, Barouni M, Saif SM. Health impact on Economy by Artificial Neural Network and Dynamic Ordinary Least Squares. J Health Man & Info. 2017;4(4):107-113.

Introduction

The study of macroeconomic data not only enriches the economic theory, but also is very important in public and private policy, so it is necessary to use better models and modern techniques more and more (1, 2).

Among the macroeconomic variables, GDP (Gross Domestic Product) is considered as one of the most important ones (3).

Although determination of the main factors affecting Gross Domestic Product is important for better priority setting, current models are not suitable enough to clarify the facilitators of economic growth rates in Iran properly (4).

Evidence suggests that oil revenue and public expenditure are the most explaining factors in Iran's economic growth. Obviously, these factors could not provide an appropriate economic structure for sustainable development (1).

Health could be one of the fundamental promoting factors on GDP. Changes in health increase the pace of growth up to 40% in industrialized countries (5), while the studies of GDP modeling in Iran often do not pay attention to health as an effective and separate variable (1-3, 6) or in the researches considering health impact on GDP, the health sector has been identified with only one indicator such as life expectancy or health expenditure (7-11). Although they are important, they cannot reflect the health sector as comprehensively as possible. In addition to these indicators, there are other important health indices that have been ignored in studies at least not as much as life expectancy or health expenditure. For example, under five year children's mortality as a helpful indicator in healthcare management (12) had a negative association with provinces of Iran by GDP per capita (13) or the number of hospital beds corrected for population size was correlated with GDP (14). But how much have they been able to improve GDP? Also, results show that the number of physicians has been one of driving healthcare expenditures in Iran (15), but the amount of its influence on GDP is not obvious (9). In other words, due

1 School of Management and Information, Kerman University of Medical Sciences, Kerman, Iran
2 Health Services Management Research Center, Institute for Futures Studies in Health, Kerman University of Medical Sciences, Kerman, Iran
3 Department of Computer, Safashar Branch, Islamic Azad University, Safashar, Iran

*Corresponding Author: *M Barouni,* Health Services Management Research Center, Institute for Futures Studies in Health, Kerman University of Medical Sciences, Kerman, Iran, Email:mohsenbarooni@gmail.com.

to some implied evidence, a better understanding of the complicated relationships between various health aspects and GDP is essential (16).

On the other hand, studies have indicated that neural networks are the most successful models for forecasting GDP with minimum errors (6, 17). Additionally, Dynamic Ordinary Least Squares (DOLS) can be another suitable technique because the factors influencing GDP are a trend (18); especially, healthcare data consist of complex pattern (19) and both of ANNs (ArtificialNeural Networks) and DOLS (Dynamic Ordinary Least Squares) could notice time dependent variables (20, 21).Therefore, the aim of this study was to investigate the health impact on Iran's economy by an artificial neural network and dynamic ordinary least squares approaches.

Method

This study was a longitudinal analytic research. The data set used in this study was a time series of annual Iran's index for the years 1961 through 2012. Whereas the aim of the study was to show the impact of health on GDP, rather than growth modeling, so by considering accessibility to health index for 50 years [1] it has made an attempt to enter variables related to health sector as much as possible [2] in order to clarify the effect of health sector. According to the previous similar studies (7-11, 22), 3 indicators (life expectancy, health expenditure and children mortality) were adopted and because of the recommendation of Salmani's research, the number of physicians and hospital beds were entered in the model (11).

Data were collected from the Statistical Center of Iran, the Central Bank of the Islamic Republic of Iran, the World Health Organization and the World Bank databases.

The following linear model was utilized to assess the relationship between health and GDP in Iran. The data were positive and difference between them was so great that we had to use logarithmic model.The following linear model was utilized to assess the relationship between health and GDP in Iran.

$$\text{Log GDP}_t=\alpha_0+\alpha_1 \log \text{DEATH}_t+\alpha_2 \log \text{BEDS}_t+\alpha_3 \log \text{LE}_t+\alpha_4 \log \text{PHYSICIAN}_t+\alpha_5 \log \text{PHE}_t$$

In this model, Gross Domestic Product (GDP) was considered as a dependent (or output) variable that showed the condition of Iran's economy. Independent (input) variables included mortality rate for children under 5-years (DEATH), the number of hospital beds (BEDS), life expectancy at birth (LE), the number of physicians (PHYSICIAN), and public health expenditure (PHE). They were adapted to show the status of Iran's health during 1961-2012. Data were collected from the Statistical Center of Iran, the Central Bank of the Islamic Republic of Iran, the World Health Organization, and the World Bank databases. Econometric analysis was performed using Eviews 7 and stata 11 softwares. The estimation of ANN model was conducted in Mathlab.

Dynamic ordinary least square

Dynamic ordinary least square is a parametric method that removes the problem of correlation between the explanatory variables and disturbance term by considering lead and lag differences. The important point in DOLS is that in these estimators, it is possible to estimate co-integration vector while times of variables are different. The other advantage of DOLS is that long-term parameter's estimation is consistence and estimators have asymptotic normal distribution; on the other hand, estimated disturbance terms do not correlate with explanatory variables in this method, so they can be considered exogenous (23). The general equation is:

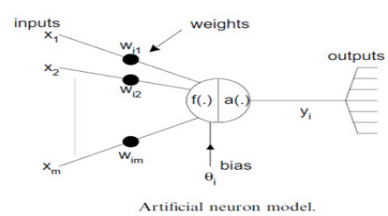
$$Y_t = A_0 + A_1 X_t + \sum_{i=-k}^{k} a_{it}\,\Delta X_{t-i} + A_2 Z_t + \varepsilon_t$$

In equation (1), Y is the dependent variable, X the vector of independent variables, Δ sign of differences and Z_t other vectors that do not need lead and lag (24).

Artificial neural network

Artificial neural network includes a large number of simple processing elements called neurons. A type of artificial neurons (AN) is shown in Figure 1.

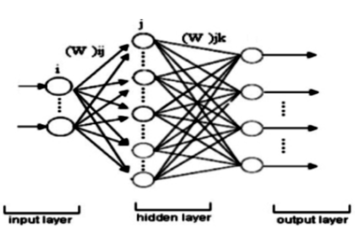
Figure 1. An artificial Neuron (16)



Every neuron has an activation function that determines its output. In Figure 1, X = (x_1, x_2,...,X_n) is input; wi represents the weight for input xi and θi is bias.

Multilevel feed-forward network is a kind of network architecture and is generally applied in prediction. A multi-layer artificial neural network includes an input layer, an output layer and one (or some) hidden layer. Figure 2 shows a multi-layer artificial neural network.

Figure 2. A multi-layer artificial neural network (16)



Neurons contact each other by connections called weights. Learning in multi-layer artificial neural network includes entering a part of data with specific output. Then, learning algorithm determines the weights to be the least error between real output and network output.

[1] The variable of health centers was omitted because it was available only for 30 years.
[2] Because the impact of import and export variables was not statistically significant, they were removed from the final model. Additional File 1 provides the details of calculations.

The process of learning will continue until the target and network output are united. The difference between objective and network output is called error. This error can decrease by changing and improving of the weights. While error becomes less than a defined amount or the number of train repetition reaches a certain level, the learning process would finish. The method of error back propagation is the learning method in which the weights of hidden layers are corrected based on the calculated error (25).

Artificial neural network used in this study was perceptron, with one hidden layer. The numbers of neurons in the input, hidden and output layers were 5, 10 and 1, respectively. Data was normalized before inputting into neural network. The validation was checked by Hold-out [3] and K-fold[4] methods and the network's performance was surveyed by means of Mean Squares Error (MSE)[5] , Mean Absolute Error (MAE)[6] , and R^2using Mathlab software.

Result:

The endogenetiy of the model's variables was detected and its results are presented in Table 1.

Table 1. Instrumental variable (2sls) regression[7] and the result of Hausman test on the model

Variable	Coefficient	Std.Error	Z	P-value
LPHE	0.36	0.04	8.14	<0.001
LDEATH	-2.12	0.14	-14.95	<0.001
LBEDS	0.20	0.09	2.24	0.025
LPHYSICIAN	0.39	0.09	4.46	<0.001
cons	-10.85	1.07	10.13	<0.001
R^2 =0.99 Root MSE=0.07	Durbin (score) chi2(1) =6.06 Wu-Hausman F(1,48) =6.07	(p=0.014) (p=0.018)		
Instrumented: LPHE	Instruments: LLE ,LDEATH ,LPHYSICIAN ,LBEDS			
LGDP : the Log of the Gross Domestic Production index LBEDS: the Log of the number of hospital beds LDEATH : the Log of the mortality rate for children under 5-years index LLE : the Log of the life Expectancy at birth index LPHYSICIAN: the Log of the number of physician LPHE : the Log of the Public Health Expenditure index				

The null hypothesis for Durbin-Wu-Hausman test was that variables were exogenous. As can be seen from the table above, variables were endogenous based on the calculated P-value of the test.

To prevent "Spurious Regressions" estimation, the unit root tests had been done to evaluate whether variables were stationary[8] and then integration Johansen test was performed. Results are reflected in Tables 2, 3 and 4.

In order to evaluate the stationary of a time series, the Augmented Dickey-Fuller unit root test could be conducted. In this method, ADF statistic is compared to Mackinnon Critical Values; if calculated value is less than the critical values, thevariable is stationary.

Table 2 provides the obtained results of unit root test on all variables in the model at level. The null hypothesis of unit root is not rejected by ADF test for all studied variables and so are the series non-stationary in the level.

From shown in Table 3, it can be seen that only the mortality rate for children under 5-years is integrated of order 2; others are integrated of order 1, so it is necessary for testing the existence of co-integration. Existing of co-integration relationship between model variables severely affects the forecast; then if there is no regression equation, the model would forecast weakly.

As can be seen in the Table 4, Max-eigenvalue test indicates 1 co-integrating equation at the 0.05 level, so the utilization of DOLS is suitable while there is only one co-integrating vector.

The results of model estimation by using DOLS method is presented in Table 5.

In summary, these result show that only the coefficient of the life expectancy at birth is not statically significant in this estimated model. D.W shows that there is no significant auto-correlation between descriptive variables. R^2, MAE and MSE indicate an estimated model used to

[3] In this method data is divided into two distinct parts; one part is considered as train data and the other part as test data. The model is produced by train data and is evaluated by test data. The ratio of every category to the total data is dependent on the attitude of the model's designer, for example, 50% proportion for both test and train or one third (1/3) for train and two-thirds (2/3) for the test.

[4] In this method, data are portioned into K classes; every time one of the k subsets is applied to test and the k-1other ones (the rest of parts) are used to train. This process repeats K times and all data are utilized exactly one time for train and one time for test. Finally, the average of the result of K times is selected as estimation. Of course, it is possible to use other ways to combine the results. It is usual to use 10-fold. In K-fold classification, the ratio and proportion of every class is tried to be equal in subset.

[5] Mean Squares Error $=MSE = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}$

[6] Mean Absolute Error $=MAE = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n}$

[7] $\text{Log GDPt} = \alpha_0 + \alpha_1 \log \text{DEATHt} + \alpha_2 \log \text{BEDSt} + \alpha_3 \log \text{PHYSICIANt} + \alpha_4 \log \text{PHEt}$
$\text{Log PHEt} = \delta + \alpha_5 \log \text{LEt}$

[8] A time series variable is stationary when its mean, variance and covariance are time independent

predict that the amount of the effect of selected indicators on GDP is reliable and exact.

Artificial neural network: the results of ANN model are displayed in Table 6.

This Table is quite revealing in several ways. First, the differences between K-fold and Hold out are highlighted in Table 5 serving 3 criteria: coefficient of determination (R^2), Mean Squares Error (MSE), and Mean Absolute Error (MAE) that make evaluation of the two methods possible. Second, R^2 shows that 99 percent of GDP changes have been explained by selected health indicators.

Third, there are very few either overestimated or underestimated values in model, according to low calculated errors between the forecasted and actual values. Fourth, Data from this Table can be compared with those in Table 4 which shows the R^2, MSE and MAE of DOLS model. Overall, these results indicate that the model enjoys a high level of precision.

To calculate the importance and effect of various input variables in the models, we used Sensitivity analysis according to the network's weight (26). Diagram 1 shows the percentage of relative importance of the variable. The number of physicians has the least proportion among the model variable, especially in the hold out method.

Table 2. Results of Unit Root Test

Variable	ADF statistic	Test critical values %5	One sided p-value	position
LGDP	0.90	-2.92	0.995	Non-stationary
LBEDS	1.61	-2.93	0.999	Non-stationary
D(LBEDS)	1.84	-2.93	0.999	Non-stationary
LDEATH	0.47	-2.92	0.984	Non-stationary
LLE	1.45	-2.92	0.999	Non-stationary
LPHYSICIAN	1.90	-2.92	0.999	Non-stationary
LPHE	-1.07	-2.92	0.423	Non-stationary

LGDP : Log of the Gross Domestic Production index
LBEDS : Log of the number of hospital beds
D(LBEDS) : first Difference of the Log of the number of hospital beds
LDEATH : Log of the mortality rate for children under 5-years index
LLE Log of the life Expectancy at birth index
LPHYSICIAN : Log of the number of physician
LPHE : Log of the Public Health Expenditure index

Table 3. Augmented Dickey-Fuller Unit Root Test on the difference variables

Variable	ADF statistic	Test critical values %5	One sided p-value	Position
D(LGDP)	-7.14	-2.92	<0.001	stationary
D(LBEDS,2)	-7.17	-2.93	<0.001	stationary
D(LDEATH)	-5.83	-2.92	<0.001	stationary
D(LLE)	-5.52	-2.92	<0.001	stationary
D(LPHYSICIAN)	-4.03	-2.92	0.003	stationary
D(LPHE)	-4.83	-2.92	<0.001	stationary

D(LGDP) : first Difference of the Log of the Gross Domestic Production index
D(LBEDS,2) : second Difference of the Log of the number of hospital beds
D(LDEATH) : first Difference of the Log of the mortality rate for children under 5-years index
D(LLE) :first Difference of the Log of the life Expectancy at birth index
D(LPHYSICIAN) : first Difference of the Log of the number of physician
D(LPHE) : first Difference of the Log of the Public Health Expenditure index

Table 4. Johansen's test for multiple co-integrating vectors

Vector	Hypotheses		Test statistics	0.05 Critical value	P-value
	H0	H1	Max Eigenvalue		
LBEDS, LDEATH, LGDP ,LLE, LPHE, LPHYSICIAN	*r = 0	r = 1	46.33	40.08	0.009
	r < 1	r = 2	24.75	33.88	0.402
	r < 2	r = 3	15.77	27.58	0.686
	r < 3	r = 4	8.97	21.13	0.835
	r <4	r = 5	5.59	14.26	0.667
	r <5	r = 6	1.66	3.84	0.198

*r indicates the number of cointegrating relationship.
LGDP : the Log of the Gross Domestic Production index
LBEDS: the Log of the number of hospital beds
LDEATH : the Log of the mortality rate for children under 5-years index
LLE : the Log of the life Expectancy at birth index
LPHYSICIAN: the Log of the number of physician
LPHE : the Log of the Public Health Expenditure index

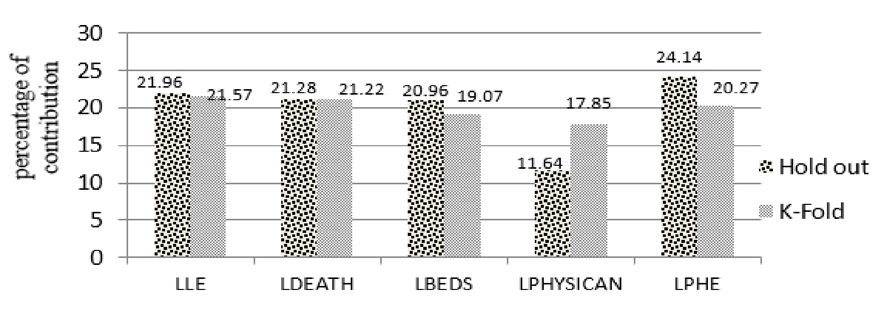
Table 5. The results of model estimation by dynamic least squares method

Variable	Coefficient	Std.Error	t-statistic	P-value
LDEATH	-1.93	0.21	-9.07	<0.001
LBEDS	0.27	0.09	2.95	0.006
LLE	0.34	0.58	0.59	0.563
LPHE	0.29	0.09	3.31	0.002
LPHYSICIAN	0.37	0.13	2.73	0.010
D.W=2.34 R^2=0.99 MSE=1×10^{-4} MAE=8×10^{-4}				
D.W : Durbin-Watson statistic MSE : Mean Squares Error MAE : Mean Absolute Error LGDP : the Log of the Gross Domestic Production index LBEDS: the Log of the number of hospital beds LDEATH : the Log of the mortality rate for children under 5-years index LLE : the Log of the life Expectancy at birth index LPHYSICIAN: the Log of the number of physician LPHE : the Log of the Public Health Expenditure index				

Table 6. The results of model estimation using artificial neural network

Cretria	Method	Total	Train	Test
R^2	Hold out	0.99	0.99	0.99
	K-fold	0.99	0.99	0.99
MSE	Hold out	1.4×10-4	6.6×10-4	1.678×10-5
	K-fold	4.9×10-4	1.18×10-3	4.1×10-4
MAE	Hold out	0.06	0.02	2.57×10-3
	K-fold	0.01	0.02	9.97×10-3
MSE : Mean Squares Error MAE : Mean Absolute Error				

Diagram 1. The contribution of variables in artificial neural network model



Discussion

Although the impact of health care sector, as the factor affecting the economic growth, has been assayed previously, its role has not received noteworthy attention by modern analysis in order to dominate the deficiency of previous researches. Therefore, this study was an attempt to investigate this role by means of more accurate and superior methods-Artificial Neural Network and Dynamic Ordinary Least Square. The findings demonstrated the considerable effect of health indices, especially children's mortality rate, on Iran GDP; therefore, it is necessary to plan for stable economic growth through considering potential factors, such as health care sector. Furthermore, this study indicated that DOLS not only could correspond to the ANN, but also provides more interpretable results.

The results of Augmented Dickey-Fuller Unit Root Test were in line with Ghorashi's finding, indicating that the variables of Gross Domestic Product, Life Expectancy at Birth, children mortality and health expenditure had been stationary in their first differences (20).

Since the variables used in the model were logarithmic, the coefficients could be interpreted as elasticity, so that it could be claimed that one percent increment in the number of doctors, hospital beds or health expenditure would increase GDP by 0.37%, 0.27% and 0.29%, respectively.

The results are in the same line with those of Hadian et al. (9). They found that the two instrumental variables (the number of physicians and hospital beds) had improved the coefficient of health expenditure in economic growth model of Iran.

The other independent variable in the model was children mortality; with regard to Table 3, one percent of reduction in the deaths of children under 5-years could improve Iran's GDP as much as 1.9%. The considerable effect of

this index clarified its significance and is in accordance with recent studies, indicating a loss of approximately 6% of non-health GDP (12). Thus, the health of children should be the first and most important duty of every nation and the major program of every government (27).
The estimated coefficient for life expectancy variable in the model of this survey was statistically not significant and it is consistent with the results of Ghorashi et al. (20), but is in contrast to the finding of Lotfalipour et al. (10). Such paradox can be attributed to non-linear effects of the variable.
An investigation in Iran revealed one percent change in health expenditure had increased 0.33 percent of non-oil real GDP (20); another study found 22% per capita income growth for one percent increase in investment in human capital health (10). Also, it was explained that 0.31% changes in GDP growth occur for each one percent change in health expenditures in the same direction (9). Minor differences between the findings can lie in the variety in the applied data because of negligible diversity of independent variable or duration of studies.
On the other hand, low proportion of health expenditure in GDP has caused lack of consideration of the effectiveness of this expenditure (7), whereas the result of researches indicated the more and significant effect of human capital on economic growth in comparison with less important contribution of physical capital on the per capita income growth (10). Although several studies have confirmed the relationship between health and economy, everyone has adapted limited and different indicators that couldn't manifest health care sector comprehensively. It is clear that this matter has a great influence on zooming out of the impact of health care sector on economy. Subsequently, provision of efficient resources for health care sector has been ignored by policy makers despite its high potential capacity to facilitate economic development and growth. This process would continue without clarification of the size effect of this sector, so it is suggested that investigations should be conducted in the field of the effective aspect of health on macroeconomic variables or compare the efficiency of allocated resource to health care sector with other sections; it should be tried to reveal the effectiveness of planning and investment in healthcare sector and finally result in the smoother way of suitable policy.
According the finding of researches, health should be considered as a top priority in policy maker's attitude, too. In fact, health expenditure is an investment, not a cost (28). In ANN model, health expenditure of public sector was the most important variable and it is in agreement with Mladenovic's (2016) findings which showed that the total health expenditure has the highest influence on GDP growth rate (22). These results further support the idea of the efficiency of this indicator in GDP modeling. However, the observed difference between the percentages of the contribution of the variables in this study was not too much. A possible explanation for this might be that other indicators of health care sector could be worthy in modeling and also investment in this sector could be affordable because improvement in health status is not limited to one aspect that is summarized in one indicator. In fact, health care sector boosts the GDP through various fields. Thus, even if enhancement in GDP due to one health indictor is small, investment is still rational.
The comparison of two methods through MSE and R^2 represented that DOLS and ANN models are nearly the same in the performance, but MAE criterion indicated that DOLS had been superior in the model's estimation, whereas neural network as an excellent technique had been more successful and accurate than other methods in modeling Iran GDP in previous researches (1, 3). Further research and various evaluation criteria can result in more exact judgment about superiority of the methods.
Perhaps, the important point in this disagreement is that Stack and Watson proved that in small samples, estimations derived from DOLS method have less Mean Square Error (MSE) than the estimates obtained from Johansen maximum likelihood. In other words, Stack and Watson, according to Monte Carlo simulation, found that DOLS had the least error in all of the estimators (29) and it is possible that superiority of neural network is due to comparison with other econometrics method.
In this study, both linear and non-linear models were adopted to overcome the complex nature of health care data, but each method had especial limitation. The first one was related to DOLS model. One of the basic problems of DOLS method was determination of the suitable lead and lag. It was difficult to find a suitable lag, while the result of DOLS estimator is sensitive to the number of lead and lag. On the other hand, there is no unique way to determine the number of lead and lag (29).
As the second limitation, the results of ANN model were difficult to interpret. Neural network model is limited to develop because of what is described as black box. It implies intricate mathematical functions in the model to describe input/output relation (30).
Also, neural networks as the soft computing approaches are data-driven models (22). This point poses a problem for such methods,the success of which is dependent on parameter selection and also the order of data observation in training.
At last, Although ANN models are good in predicting, they are so complicated and vague in interpretation, whereas strategic planning needs precise analysis and explicit concepts. On the other hand, DOLS model was not as flexible as ANN in dealing with data, but its result was clarified. Thus, it seems that a combination of the two methods in future researches might be a solution to remove these limitations.

Conclusion

Changes in health indicators (as a consequent of the health care sector's performance) have altered the GDP in Iran. Therefore, modeling in order to quantify these influences makes planning for development more achievable and more accurate and interpretable modeling of these influences would improve the positive attitude to healthcare sector.

Conflict of Interest

None declared.

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