NEURAL NETWORK FORECASTS OF TAIWAN BUREAU OF NATIONAL HEALTH INSURANCE EXPENDITURES

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ABSTRACT

This study predicts the medical expenditure of national health insurance by a Back-Propagation Neural Network (BPN). Monte Carlo Simulation and Multiple Regression Analysis are used to compare the results of the BPN. Empirical results show the performance indicator modeled on BPN is the best, followed by those modeled on Multiple Regression Analysis and Monte Carlo Simulation. In estimating the opportunity cost that will be lost when the forecasting model overestimates the expenditure, and the resource cost that will occur when the model underestimates the expenditure, the Monte Carlo Simulation and Multiple Regression Analysis are likely to be better forecasting methods. Finally, the three key factors affecting medical expenditure are the aging population index, the inflation rate and the number of insured population. This study makes a contribution extant literature by using a BPN to predict the medical expenditure performance indicator error rate. A BPN is better than other models in terms of TIC, but may not be the best forecasting method in a variety of cost conditions.

JEL: C53, G22, G28

KEYWORDS: Medical Expenditure Forecasting, Back-Propagation Neural Network (BPN), Monte Carlo Simulation, Multiple Regression Analysis

INTRODUCTION

Taiwan implemented a National Health Insurance (NHI) program in 1995. After adjustments in the health insurance costs, outpatient co-payments, and reimbursement of medical costs, the NHI has moved steadily towards sustainability. The NHI program is one part of Taiwan's social security system, and is a program of risk diversification and premium sharing. The proportion of the population covered by health insurance has now reached 99%, and the reported satisfaction of the public has now reached 80%. However, due to an aging population, increased medical needs and other factors, this health insurance program incurred a financial deficit in 1998. Since 1998, the NHI has begun to show shortfalls and in December 2008 the NHI was 155.9 billion New Taiwan Dollars negative. Every year, there is a 34 billion gap for the period (Department of Health 2009) and financial loss has now become a major issue for the Taiwan NHI. Whether the NHI program can continue with sustainable development depends on the soundness and balance the NHI system finances. The National Health Insurance Bureau is currently committed to implementing a second-generation health insurance plan, but the longer the current health insurance scheme continues, the greater the financial shortfall. Therefore, the motivation of this study is to understand key factors affecting healthcare finance and reduce prediction errors.

In recent years, spending on health care has continued to rise, exceeding the revenue from health insurance premiums, thus continually increasing the deficit (National Health Insurance Administration of Taiwan 2008). To avoid bankruptcy of the NHI program, the main causes of rising medical expenses must be identified. Newhouse (1977) adopted the Organization for Economic Cooperation and Development

(OECD) economic data from 13 countries to explore the relationship between per capita GDP and medical expenditure. The main finding was that more than 90% of health care expenditure used income as the main independent variable and other non-income variables were not important. Leu (1986) also discussed the "income variable" and "non-income variable" using the same data. To control medical expenses, it is necessary to understand the factors of medical expenditures to correctly predict the medical expenditure and then solve the health care deficit. Health insurance is a main benefit in Taiwanese society. So when there is a deficit in healthcare finance changes are called for. However, increasing healthcare rates or demand-side cost-sharing, would result in public outcry. Prevention of the deterioration of healthcare finance should start with medical expenditures. Therefore, to predict health care costs, it is crucial to control the growth in health spending.

LITERATURE REVIEW AND RESEARCH DEVELOPMENT

Most predictive literature use a single research method. This study uses three methods and compares their predictive ability. In the literature, prediction models are diversified. Scholars used to apply the artificial neural networks (NN) prediction model. With high processing speed and fault tolerance, the data is easy to build and practical. Diane (1990) and Henson, Huxhold and Bowman (1992) pointed out the advantages of using a neural networks to predict. These advantages include the non-linear conversion function, being able to constantly repeat the study sample and weight value adjustment. Tang and Peng (2002), and Chen, et al., (2008) applied artificial neural networks when forecasting agricultural products. Monica (2004) used an artificial neural network to predict common shareholders' equity; Qing, Karyl and Marc (2005) adopted a univariate and multivariate neural network to predict stock returns on the Shanghai Stock Exchange. Lin et al. (2006) used a neural network to predict the MICU patient survival rate. Chen et al. (2006), examined National Health Insurance medical expenses censorship. They used a logistic regression analysis and neural network analysis comparison of misclassification costs as the basis for their assessment. The neural network model showed a better classification result. Zou et al. (2007) compared ARIMA, neural networks, the linear integrated model for wheat forecasting performance, price turning points and profit criteria for judging. The neural network model produced the best results. Yeh, Tung and Chang (2009) used neural networks in hospitals to forecast outpatient missed appointments.

In addition, Chou (2000) pointed out that health care costs are more concentrated on the elderly by using a multiple regression analysis to assess patients in past and present medical use. Liao and Lu (2000) used a multiple regression test analysis on stroke patients during their hospitalization and the effectiveness of medical expenses, with the empirical results that case management can effectively control the length of hospital stay and medical expenses. The results of Chung et al.'s (2003) stepwise multiple regression analysis of NHI resource usage for users of home care in 1997, pointed out that outpatient visits account for 40% of the total variance of outpatient costs providing a public health decision-making reference. Tsai et al. (2007) assessed the impact of foreign workers on Taiwanese hospitalization behavior, using multiple regression and logistic regression to explore various independent variables used to predict hospitalization.

Research in the insurance field sometimes uses the Monte Carlo Simulation method to estimate the maximum possible loss. This approach uses probability distributions to repeatedly simulate the frequency of annual losses. Pentikäinen (1983) used Monte Carlo Simulation to analyze insurance companies' marginal liquidity and cash flow. Chih-Chou Chiu et al. (2006) used the Markov Chain Monte Carlo Hierarchical Bayesian neural network to estimate product reliability and distribution failure time to verify its suitability and accuracy for predictive value of the product life reliability model. Qing and Parry (2009), used 45 quarterly accounting variances from 283 companies to construct a predictive model, suggesting the Monte Carlo assessment of genetic algorithms (GA) could lead to suitable model parameters. BPNs and GAs were adopted to predict and compare quarterly surpluses per share. Therefore, the Monte Carlo Simulation is also highly regarded as one can participate in the prediction method.
Neural network, multiple regression analysis and Monte Carlo methods are often used. This study uses

three models for the prediction analysis of medical resources. Predictions of these methods have advantages and disadvantages. Real, Kevin and Rustam (2008) pointed out that a neural network cannot be statistically significantly better than the regression model. Doong and Lee (2009) illustrated that the prediction of multiple regression is less than the Monte Carlo method. Yeh et al. (2009) advocated that the predictive ability of a neural network is better than regression. Therefore, this study intends to calculate the mean absolute percentage error (MAPE), the forecasting error rate and the inequality coefficient (TIC) to judge the accuracy of these models, and the pros and cons of the three predictions.

In addition, the difference between this study and other literature is that most literature has merely addressed the level of forecast accuracy, but rarely dwells on the degree of post-prediction errors, which may result in overlooking the impact of error cost. Therefore, in addition to assessing the margin of error of the predicted value and the actual value, we also consider the opportunity cost and resource cost. We compare which has the better prediction ability among these prediction methods.

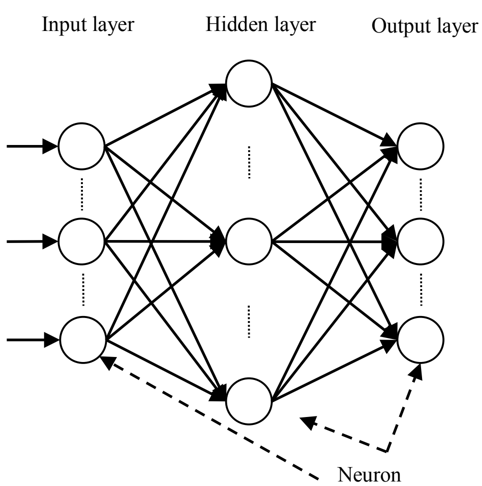
The empirical results show that evaluating performance errors, BPN is better than a multiple regression and the Monte Carlo method. If further analyzing the cost of over-prediction, the best prediction methods may be Monte Carlo, and multiple regression analysis. This study suggests that health insurance medical expenses may be affected by the aging population index, rate of inflation, and the number of the insured population. The contribution of this research study is the ability to predict health insurance medical expenses. If cost conditions are not established, the BPN error values are relatively smaller than for other models. However, if the cost condition is set, the other models may be superior to the BPN.

DATA AND METHODOLOGY

The Back-Propagation Neural Network (BPN)

The BPN is the most common neural network learning model. This study uses the main model of BPN, as constructed, to predict NHI expenditure. The BPN network structure is constituted of an input layer, several hidden layers and an output layer. The model is shown in Figure 1.

Figure 1: BPN Model Structure



Source: Karayiannis and Venetsaopoulos (1993). This study uses this method to construct the main model to predict NHI expenditure. Its predictive power in most studies is very good.

Input layer is used to represent the input variables of the network, the number of processing units according to the questions and using a linear transfer function. Hidden layer shows the interaction among processing units. The number of processing units must be decided on a trial basis. The hidden layer is non-linear transfer function. The hidden layer can be more than one layer or no layer at this level. In general, selection of the number of processing units in the hidden layer follows three methods. These three methods are a.) average method = (input layer processing unit + output layer processing unit) / 2; (b) total method = (input layer processing unit + output layer processing unit); and c.) the doubling method = (input layer processing unit + output layer processing unit) × 2. The process is to adjust combinations to select the number of processing unit in the hidden layer. However, Chi and Chen, 2001 find the more complex the problem, the more hidden layer units are needed. (Ye 2004). Output layer is the non-linear transfer function. This layer represents the network output variable. The number of processing units depend on the questions.

Network calculus: BPN calculation process can be divided into two stages: the learning stage and recalling stage (Yeh 2004). The learning stage: when computing has deviation between the network inference and target values, according to the network learning algorithm, learning paradigms adjust weigh values of the network link to reduce the error between the actual value and the correct value. The formula (1) as follows:

$$E = \frac{1}{2}\sum_{j}^{m}(T_j - A_J)^2 \tag{1}$$

T_j = Target output value of the output layer, A_j = Inference output value of the output layer. The BPN learning process is mainly with the weight value updates and adjustment. When the network learning error is below the tolerance, which means that the neural network training is completed, it will enter the network recall stage. The recall process (testing process): at the end of the learning process, the network will follow the recalling algorithm to input data to determine the network output data. This process inputs the trained weight values into the test samples through the layers of the weighted value, aggregate operations, functions, and conversion process. The efficacy of the network performance can be gained by comparing the actual output value and the expected output value.

The number of layers in the network: Network layers; two or three layers can form a network. The research model input is regarded as a single layer and may also add a hidden layer and output layer to become a two or three layer network. The decision regarding the number of hidden layers: the contribution of BPN is that there are hidden layers. However, the decision regarding the number of hidden layers has no set rules to follow, thus it is subject to adjustments according to the complexity of the problem. In general, the number of hidden layers is set from one to three layers, and the convergence effect of the network is the best.

The decision regarding the number of processing units; firstly, the input layer: the decision of the number of processing units depends on the input variables. Usually the number of the input variables is the number of the processing units. The hidden layer: the higher the number of processing units of the hidden layer, the slower the convergence speed; however, it is easy to get a smaller error value. If the processing unit exceeds a certain number, reducing the error is pointless as computing time is only prolonged. To avoid this situation happening, in general, the trial and error method has the best network performance. In practice, the processing units of the hidden layer are judged by past experience. The output layer is the major predictive target value. For example, this study aims to predict 12 cases of NHI monthly expenditure for 2008. There is only one feedback output value and thus only one processing unit.

Related parameter settings: Momentum factor α, also known as the "momentum", is the weight correction plus part of the proportion of the previous weight value correction amount to be calculated. This can improve the oscillation phenomenon in the training process and accelerate network convergence. Its role as a low-pass filter not only allows the network to ignore the very small changes in the error curve but also to respond to the latest trends. Epoch size, also known as "iteration value" or "training time", is the time of the cyclic training. One epoch is gained when all input data completes the network learning process. Learning rate, η: If the learning rate is too large or too small, it is not conducive to the network convergence effect. If the learning rate is larger, then the network weight value correction amount will be greater, and can accelerate the function's approach to its minimum. If the learning rate speeds up, however, it may also make the network less stable.

Monte Carlo Simulation

Mainly target (NHI medical expenses) random assessment, using the computer random sampling, analog millions of time the subject of health insurance medical expenses, plus total convert may mean NHI expenditure value, to get self-expected expenditures. The procedure is as follows: select the subject of health insurance medical expenses are incurred model, the mean and standard deviation, the lognormal formula (2) shown:

$$S_t = S_{t-1} e^{\left(r-0.5\sigma^2\right)\Delta t+\sigma\varepsilon\sqrt{\Delta t}} \tag{2}$$

S_{t-1} is the prior target medical expenditure; σ is NHI expenditure standard deviation; Δt is the time interval between each time a medical expenditure incurs. ε stands for a standard normal random number. (2)The next medical expenditure incurs after extraction of the random numbers ε. Repeat the process and a medical expenditure route and the expenditure expiring value are obtained. 3) Repeat the process N times and N mean values of target medical expenditure are obtained. 4) The current NHI expenditure predictive value is gained by discounting the mean values at the risk-free interest rate.

The Multiple Regression Analysis

Multiple regression is used to join two or more independent variables in the regression equation. Multiple regression has been widely used in the fields of science, management, engineering, medicine. Multiple regression must assess model adequacy by checking the residuals compliance with normality, equal variance, residual independence, adequacy of the linear mode, and the presence of outliers. In Equation 3, y represents the dependent variable, β multiple regression coefficients, x the independent variable and ε represents a random error:

$$y = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k + \varepsilon \tag{3}$$

Performance Indicators

Variables $\hat{Y}_i$ in the formula for performance indicators are for the i prediction model expectations. Y_i is for the first actual value, $\hat{Y}_i - Y_i = \varepsilon_i$ for the i random error, and n to predict the number of samples. Equation 4 is the calculation for the performance indicators:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{Y}_i - Y_i}{Y_i}\right| \times 100 \tag{4}$$

The average absolute error rate (MAPE) measures the percentage of the unexplained portion of the model. It also assesses the prediction merits of the indicators. Equation 4 is a relative value and not the actual measurement value. The estimated value in the unit or the high and low values can be objectively the relative difference between the actual and predicted values. MAPE close to zero, implies the measurement accuracy of the prediction model estimation results is better. The Lewis (1982) indicators are divided into four levels: less than 10% is an accurate prediction; between 10% and 20% represents a good prediction; between 20% and 50% indicates a reasonable forecast; more than 50% indicates a poor prediction.

Theil (1996) used Equation 5 to assess the statistical indicators of the predictive value. The process mainly involved the measurement of deviation between the simulated variances and their time paths. A relative value between 0 and 1 was obtained from the division of numerators by denominators. Zero indicated the actual value was equal to the predictive value, i.e., the predictive model was perfect. If the TIC value is 1, the predictive efficacy of the model is not satisfactory. TIC is used, rather than the mean value of predictive errors, to measure the relative error that can lead to minimum predictive errors. Therefore, the smaller the TIC value is, the smaller the predictive errors, and the greater the predictive capability.

$$\mathrm{TIC} = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(\hat{Y}_i - Y_i\right)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Y}_i\right)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i\right)^2}}$$

<u>Prediction Model Variables and Data Description</u>

We begin by discussing the explanatory variables. Newhouse (1977) pointed out the factors that affect personal health care costs are largely attributable to an individual's personal health status. Van and Ellis (2000) thought that understanding the relative variation of medical costs requires the use of a variety of risk factors to construct a risk-adjusted model combination. Medical expenses are not only the premedical costs, but are also affected by the impact of other factors, such as demographic factors, medical resources, self-health assessments and general economic circumstances.

As an overview of the above, this study refers to Hsu, Yang and Fan (2005) to discuss medical expenses, using four dimensions of factors to predict: (A) demographic: insured population, average insured payroll, the aging population index; (B) medical resources: the number of authorized medical institutions; (C) self-reporting: crude death rate; (D) macroeconomics: inflation rate, unemployment rate. These variables are described below:

Hsieh, Lin and Yo (1998) indicated that the effect of income also included the insured population. The ratio of insured population has a positive correlation with medical expenditure. Ji (2001) pointed out the number of the insured population is one demand-side factor that affects NHI expenditure. An increase in the number of insured population causes medical expense increases. Yang, Lee, and Chiou (2004) pointed out that an increase in the insured population number leads to an increase in medical expenses and has a significant influence. Consequently, this study selected the number of the insured population as an input variable.

The next independent variable is average payroll salary of the insured population. Newhouse (1977; 1992) pointed out that increasing income increases health care spending which is normally good, and considers factors caused by rising health care costs. The resulting increase is the most important factor. Ji (2001) is also of the view that national income variables explain medical expenses. Sue et al. (2003) indicated that the average insured salary of the insured population is an important factor for the assessment of health care expenditure. Since the related information available is annual data, this study refers to the method adopted by Xu et al. (2005), using the average monthly insured salary amount as income's substitute variables.

The next independent variable is the aging population index. Population aging means that, during a period of growth, the proportion of elderly population in the total population of a region increases. Hitiris and Posnett (1992) found that, of the elderly population, the proportion aged more than 65 years showed a significantly positive correlation with medical expenses. Mruthy and Ukpolo (1994), Xie et al. (1998), Herwartz and Theilen (2003), and Lin, Shu, Huang (2007) came to the same conclusion. Therefore, the aging population index is an important variable affecting the growth of health insurance medical expenses.

Next we consider the number of authorized medical institutions. The number of authorized hospitals has gradually declined from 783 in 1995 to 504 at the end of 2008. However, the number of contracted clinics has increased from 13,816 to 18,325 by the end of 2008, an increase of 4,509. Special medical care institutions (i.e., pharmacies, medical laboratory institutions, home care agencies, midwifery, community psychiatric rehabilitation, physical function treatment, clinics of medical radiology, etc.) increased from 1,063 at the end of 1995 to 5,045 at the end of 2008, an increase of 3,982. These figures shows the changes in the number of hospitals have a complementary relationship with the changes in the number of clinics. Overall, hospitals are geared toward large-scale expansion and clinics toward the development of the population. Therefore, the allocation of medical resources is influential (Central Health Insurance Corporation 2008). Huang (2001) pointed out that as Taiwan's population is aging, medical needs can be guided by the supply of medical resources. Increasing the supply of medical resources will increase the amount of health care services and increase medical expenses. Lin et al. (2007) believed that mortality would significantly affect the number of authorized medical institutes, which in turn impacts the increase in medical expenditure. Consequently, mortality is an important indicator of national health. Therefore, this study adopts mortality as an independent variable in the model predicting medical expenditure.

Mortality is an important variable in the model. Hitiris and Posnett (1992) found a trend of increases in medical expenditure months before a research object died. Jenkinson, Coulter and Wright (1993) and Takeuchi et al. (1995) found that mortality and morbidity rates, regardless of the subjective and objective perspectives are the best indicators to measure health. Mortality rates indicate whether physical and mental health of the people in an area are in good condition. This is closely related to health insurance expenses. Lin et al. (2007) reported that mortality significantly affects the number of special medical institutions, while the numbers of medical institutions also affects the increase in medical expenses. Therefore, mortality is an important indicator to measure the national health situation. Mortality variables were included in the prediction model to evaluate health insurance medical expenses.

Next we consider the inflation rate. When inflation is rising, the nominal price of drugs and medical equipment cost more. Rises also increase the salaries of staff and hospital administration costs. If prices increase, there is a rising trend for total health care costs. Newhouse (1992) reported that human capital prices rose faster than the general price level, and price increases will inevitably bring about increased health care costs. The findings of Gerdtham et al. (1992) and Karatzas (2000) were the impact of health care expenditure growth factors are focused on average and real GDP per person, health care price index and other factors. As a result, this study takes the inflation rate as affecting price changes and as a variable that influences input of medical costs.

The unemployment rate is included in the model. Newhouse (1997), Gerdtham et al. (1992) and Hitiris and Posnett (1992) used the unemployment rate to predict medical expenses. The empirical results of Chen and Qiu (2003) stated that an increase in unemployment will make medical care spending significantly grow. Therefore, this study selects the unemployment rate as a variable when assessing the predictive model of medical expenditure.

A data resource variable is included in the model. The study period was from January 1996 to December 2008. Some 156 monthly data observations were used to establish the main assessment of the health insurance financial forecast model. Variables used include the number of the insured population, average insured salary, aging population index, number of authorized medical institutions, mortality rate, inflation rate and unemployment rate. Taiwan started the NHI program in March 1995 and. Due to limited data availability in 1995, the sample data begins in 1996.

The dependent variable data is actual health insurance medical expenses (from 1996 to 2008 National Health Insurance Statistics Annual monthly medical expenses). The unit of measurement is: 100 million New Taiwan dollars. Next we discuss additional independent variables.

Independent variable data is (A), the insured population was taken from the National Health Insurance Statistical Yearbook. The measurement unit is million people. (B) The average insured salary was obtained from National Health Insurance Statistical Yearbook. The Unit of measurement is $10,000 New Taiwan dollars. (C) Aging population index data were obtained from the economic statistical database of the Ministry of Education AREMOS "ROC national income database". The formula is "the total population over 65 years old," divided by "the total population of the Republic of China"× 100%, unit: %. (D) The number of authorized medical institutions were obtained from National Health Insurance Statistical Yearbook. The unit of measurement is 10,000 institutions. (E) Mortality rates were obtained from the economic statistical database of the Ministry of Education AREMOS "ROC national income database". The variable is calculated as the number of deaths divided by "the total population of the Republic of China" × 100%, unit: %. (F) Inflation data were obtained from the economic statistical database of the Ministry of Education AREMOS "ROC national income database", i.e. (Current CPI index “minus” a previous CPI index) divided by "a previous CPI index" × 100%, unit:%. (G) Unemployment rate data were sourced from Ministry of Education AREMOS economic statistics database "database of the Republic of China national income", that is the "unemployed population" divided by "the total population of the labor force in the Republic of China" × 100%, unit:%. Table 1 shows summary statistics of the data.

Table 1: Summary Statistics

	Min	Max	Mean	S.D
Actual health insurance medical expenses	145.09	408.49	267.62	55.68
The insured population	20.04	22.85	21.68	0.85
The average insured salary	21.42	25.63	23.52	1.24
The aging population index	7.92	10.49	9.11	0.80
Number of authorized medical institutions	1.77	1.99	1.87	0.08
Mortality rate	5.54	6.25	5.85	0.21
Inflation	-0.28	3.52	1.26	1.17
Unemployment rate	2.50	5.20	3.75	0.91

Source: The present study. The descriptive statistics of the variables used by this study as the overview of the data.

Comparison Cost of Prediction Error Levels

Most documentation discusses prediction accuracy of the predicted value margin of error. The actual value has not been the subject of an in-depth analysis that might ignore the size of the error related costs. Therefore, this study featured three prediction model output results by Yeh (2009), who evaluated the cost analysis as follows:

$$\sum|\varepsilon_i \; X \; A|, IF \; \varepsilon_i > 0; \; \sum|\varepsilon_i \; X \; B|, IF \; \varepsilon_i > 0 \qquad (6)$$

Random errors i in the equation (6) $\varepsilon_i = \hat{Y}_i - Y_i$, $\hat{Y}_i$ is i prediction model expectations, Y_i for i actual value.

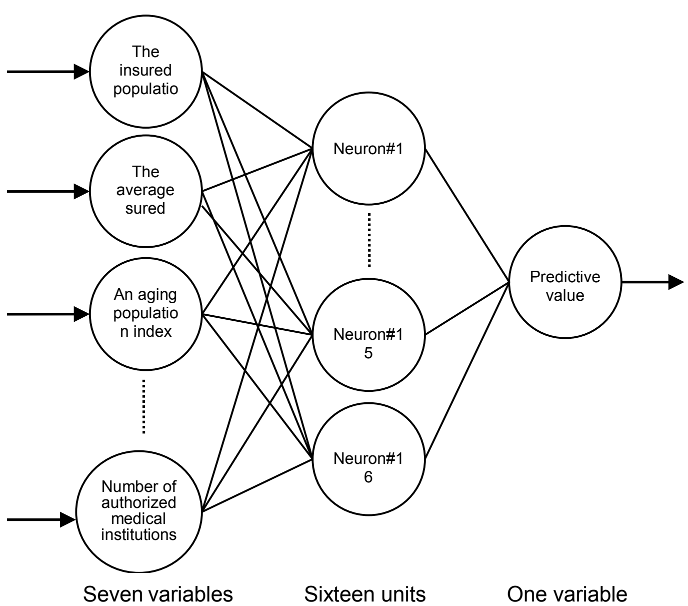
RESULTS AND DISCUSSION

Back-Propagation Neural Network Methodology

In this study, monthly data from 1996 to 2007 was used as a training sample of 144 observations, and the twelve monthly data points from 2008 was used as a validation sample. Figure 2 shows the structure model used to predict health insurance medical expenses. The model is divided into three stages. The first stage sets the input layer into seven independent variables, and the output layer is set to a contingency number. The second stage is setting the hidden layer. Due to the high complexity of the NHI items of expenditure, it was necessary to use a doubling method, added by doubling the input neurons (7 independent variables) and the output neurons (1 dependent variable) for 16 units of the first layer. The hidden layer is set 'three layers' deep as a structure, and is based on Shaikh and Zahid (2004), who suggested that setting the hidden layer, (i.e., the second layer) meant the number of neurons was twice that of the first layer. Three hidden layers were set to 16 units, 32 units, and 1 unit. The third stage, using "health insurance medical expenses", uses a predictive value (a dependent variable) as the output layer.

To identify the MAPE and TIC minimum values we use the alpha of 0.1,0.2,0.3,0.8,0.9 and Epoch containing 150,250,500,600,750,800,1000, and six η of 0.01,0.05,0.1,0.25,0.8,1. An attempt was made to identify various combinations of minimum error value. The total simulation was run up to 10,500 times ($5 \times 7 \times 6 \times 50 = 10{,}500$). The research results are shown in Table 1. When the parameters set α=0.2, Epoch=500 times, η=1, the optimal performance indicators of MAPE=3.94 and TIC=0.02 can be obtained. Therefore, we suggest this result as a basis for the BPN forecasting model of health insurance medical expenses.

Figure 2: BPN Forecasting NHI Medical Expenses Model Structure



Source: The present study. We can know the predictable results of NHI expenditures by the BPN model.

Table 1: BPN Various Parameters and Performance Indicators in 2008

A	Epoch	Perf. index	η 0.01	0.05	0.1	0.25	0.8	1
0.1	150	MAPE	4.198	6.284	5.442	6.001	5.449	5.531
		TIC	0.030	0.036	0.035	0.035	0.036	0.033
	250	MAPE	5.442	5.037	5.472	5.031	4.971	4.843
		TIC	0.041	0.035	0.033	0.031	0.032	0.033
	500	MAPE	3.636	5.404	4.886	4.917	5.450	5.111
		TIC	0.030	0.036	0.034	0.030	0.032	0.035
	600	MAPE	4.199	5.265	4.614	5.438	4.089	4.819
		TIC	0.029	0.035	0.031	0.042	0.026	0.033
	750	MAPE	5.133	5.037	5.744	4.208	4.599	4.269
		TIC	0.034	0.032	0.033	0.032	0.031	0.031
	800	MAPE	5.536	3.880	5.228	6.011	5.031	6.175
		TIC	0.034	0.027	0.031	0.035	0.031	0.034
	1,000	MAPE	4.910	4.688	4.579	5.602	5.869	5.253
		TIC	0.031	0.026	0.033	0.038	0.033	0.033
0.2	150	MAPE	4.884	5.698	4.690	4.330	5.115	5.811
		TIC	0.034	0.036	0.035	0.027	0.034	0.035
	250	MAPE	5.503	5.254	4.815	6.440	5.261	4.825
		TIC	0.033	0.036	0.031	0.040	0.033	0.032
	500	MAPE	4.198	5.076	5.077	5.986	5.449	3.936
		TIC	0.030	0.038	0.035	0.039	0.036	0.025
	600	MAPE	7.213	6.033	5.472	5.031	4.971	5.905
		TIC	0.044	0.035	0.033	0.031	0.032	0.035
	750	MAPE	5.159	5.552	11.201	4.917	4.897	4.576
		TIC	0.033	0.033	0.065	0.030	0.036	0.030
	800	MAPE	5.008	5.854	4.854	4.379	5.600	4.819
		TIC	0.036	0.037	0.029	0.031	0.033	0.033
	1,000	MAPE	6.778	4.921	5.931	4.269	5.536	3.880
		TIC	0.041	0.031	0.033	0.031	0.034	0.027
0.3	150	MAPE	6.515	4.821	4.531	4.921	6.714	4.286
		TIC	0.039	0.033	0.030	0.036	0.045	0.032
	250	MAPE	5.253	4.884	4.552	4.690	5.851	4.330
		TIC	0.033	0.034	0.036	0.035	0.037	0.027
	500	MAPE	5.115	4.819	5.254	4.815	7.086	6.423
		TIC	0.034	0.035	0.036	0.031	0.038	0.041
	600	MAPE	5.261	5.606	4.846	4.144	5.576	4.788

α	Epoch	Perf. index	η 0.01	0.05	0.1	0.25	0.8	1
0.3	600	TIC	0.033	0.045	0.029	0.026	0.034	0.031
	750	MAPE	5.550	4.198	5.077	8.424	5.449	3.936
		TIC	0.039	0.030	0.035	0.051	0.036	0.025
	800	MAPE	7.849	4.971	5.031	4.810	5.061	6.099
		TIC	0.050	0.032	0.031	0.030	0.034	0.041
	1,000	MAPE	6.995	6.295	4.917	4.576	5.111	4.490
		TIC	0.043	0.040	0.030	0.030	0.035	0.037
0.8	150	MAPE	5.037	5.919	5.047	5.600	5.817	4.854
		TIC	0.032	0.042	0.034	0.033	0.034	0.029
	250	MAPE	10.267	5.122	8.664	4.269	4.875	4.885
		TIC	0.059	0.035	0.046	0.031	0.029	0.035
	500	MAPE	7.526	4.531	4.986	5.894	5.739	5.246
		TIC	0.049	0.030	0.034	0.038	0.040	0.035
	600	MAPE	5.739	5.869	4.552	7.087	4.690	7.300
		TIC	0.033	0.033	0.036	0.045	0.035	0.039
	750	MAPE	6.423	14.186	4.815	5.254	4.819	9.800
		TIC	0.041	0.072	0.031	0.036	0.035	0.053
	800	MAPE	5.606	4.846	10.621	4.144	4.673	4.788
		TIC	0.045	0.029	0.063	0.026	0.031	0.031
	1,000	MAPE	4.846	4.144	5.576	4.788	6.991	5.834
		TIC	0.029	0.026	0.034	0.031	0.042	0.039
0.9	150	MAPE	5.514	5.000	4.951	5.474	6.657	4.782
		TIC	0.036	0.033	0.032	0.030	0.050	0.032
	250	MAPE	7.459	5.115	5.928	3.852	4.746	6.639
		TIC	0.051	0.032	0.037	0.032	0.034	0.042
	500	MAPE	5.043	4.743	5.569	7.696	6.195	5.731
		TIC	0.030	0.034	0.035	0.049	0.035	0.033
	600	MAPE	4.629	8.792	4.572	5.036	8.316	5.901
		TIC	0.033	0.051	0.031	0.031	0.050	0.039
	750	MAPE	5.266	5.833	5.922	6.329	8.722	4.809
		TIC	0.030	0.039	0.036	0.037	0.051	0.032
	800	MAPE	5.449	5.422	8.418	5.972	5.640	6.192
		TIC	0.036	0.037	0.045	0.034	0.037	0.033
	1,000	MAPE	5.581	6.608	4.419	5.177	4.371	11.331
		TIC	0.038	0.043	0.032	0.034	0.034	0.061

Monthly data from 1996 to 2007 was used to establish a predictive model using BPN, with 2008 as a predictive assessment period. MAPE closer to zero implies measurement of the predictive model is better. A small TIC indicates a small predictive error and the predictive ability is good. When the parameters set α=0.2, Epoch=500 times, η=1, the optimal performance indicators MAPE=3.94, TIC=0.02 can be obtained. This study suggests the result as a basis for a BPN forecasting model for health insurance medical expenses.

This study adopted the inertia factor 0.2, the number of learning times at 500, and the learning rate of 1 in the BPN forecasting model. While other conditions remain unchanged, the process is to delete one after another in the following sequence: the independent variables of the insured population, monthly insured salary amount, aging index, number of authorized medical institutes, mortality, inflation rate and unemployment rate. Then, the BPN error values are assessed and used to decide which independent variable has the biggest impact on the predictive outcome. From Table 2, if the model only deletes the aging population index, the predictive value and the actual value of the MAPE are up to 8.173. Therefore, the aging population has the highest influence on the index of the overall model. In addition, MAPE is 4.807 after deleting the number of authorized medical institutions. Thus, the most important three main causes affecting NHI medical expenses, respectively, are the aging population index, the inflation rate, and the insured population. Consequently, the relevant government authorities may adopt the recommendations of this study as a policy reorientation and design.

<u>Monte Carlo Simulation</u>

This study used different simulation times (50, 100, 250, 500, 750 and 1,000) to predict NHI expenditure. The results are shown in Table 3. The Monte Carlo Simulation predicted the value of medical expenses for the months of 2008. There is a departure from the real NHI expenditure and performance indicators were used to measure the degree of prediction errors. The results showed the performance indicators from different times of simulation are very similar. After 750 simulations, the performance indicators are better. The result of the Monte Carlo Simulation is the assessment of the NHI expenditure model.

Table 2: Using Itemized Delete Method to Assess Important Variables of BPN

Delete Variables	The Insured Population	The Average Insured Salary	An Aging Population Index	Number of Authorized Medical Institutions	Mortality Rate	Inflation	Unemployment Rate
January	360.89	380.58	338.65	337.72	331.32	334.18	342.52
February	364.22	365.81	344.86	341.71	326.74	314.19	323.41
March	364.81	335.47	336.92	339.37	331.38	341.47	345.77
April	334.44	344.70	326.70	340.59	338.80	314.98	343.57
May	339.13	364.25	325.47	337.61	339.04	323.44	351.20
June	318.24	358.62	337.05	346.21	341.11	310.05	343.77
July	329.58	348.18	321.40	339.50	340.13	318.19	355.34
August	330.18	351.14	319.41	338.69	340.57	321.41	360.46
September	332.35	317.86	313.01	338.30	342.16	328.14	370.63
October	323.09	378.50	335.51	352.92	343.44	310.33	344.76
November	352.52	317.72	324.46	339.44	327.71	356.73	375.39
December	368.11	317.78	322.91	342.48	319.68	368.56	371.32
MAPE	6.940	6.718	8.173	4.807	5.644	7.788	5.630
TIC	0.045	0.045	0.048	0.032	0.040	0.049	0.032

To understand the order of importance of variables for the BPN model, the itemized deletion method was used that removes a variable for predicting the level of error. Using the monthly data of 144 observations from 1996 to 2007 as a training sample, then, using monthly data of 12 observations in 2008 as a validation sample, six independent variables were input as the neurons, three hidden layers are set to 14, 28, 1 and output neurons as a dependent variable to construct the BPN network level. Additionally three important parameters were set: inertia factor of 0.2, learning 500 times, and the learning rate of 1. Models for various variables are deleted for seven groups, each simulation analysis is run up to 50 times, 350 results in total are shown above.

Multiple Regression Analysis

We observe the residual errors of the dependent variable. Actual medical expenditures show no serious deviation from the 45-degree line. Thus it is possible to claim the normality assumption is valid. Additionally, standardized predicted values and standardized residuals showed random distributions. Therefore, the assumption of independent and equal variance is established. In addition, for the other independent variables, continuous variables are adopted, including the insured population, the average payroll of the insured population, aging population index, the number of authorized medical institutions, the mortality rate, inflation rate, and unemployment rate. Equation 7 shows the results:

$$\widehat{DLHE} = -527 + 41.7\widehat{IP} + 44.2\widehat{DLAIW} \widehat{+66.9}\ \widehat{AGE} - 27.0\widehat{CMCI} + 0.66\widehat{CDR} + 0.94\widehat{SIR} - 704\widehat{UR} \quad (7)$$

(-1.97)* (2.20)** (0.70) (0.06) (-0.39) (1.03) (0.26) (-0.06)

Only the independent variable, insured population's P-value reached significance of 5%. The overall R2 was 22.08%. After the adjustment, R2 equaled 18.069%. The F-value was 5.05, achieving a 10% significance level. An R2 22.08 is not particularly high. The result is still within the acceptable range per the forecast of Chou et al. (2000) where the multiple regressions R2 was around 20%. Finally, using a multiple regression model to predict twelve monthly observations in 2008, the calculated performance indicators are MAPE 6.345, and TIC of 0.0043 (Table 4). The result was used as one of the comparative models to predict medical expenditure.

Comparison of Prediction Model Results

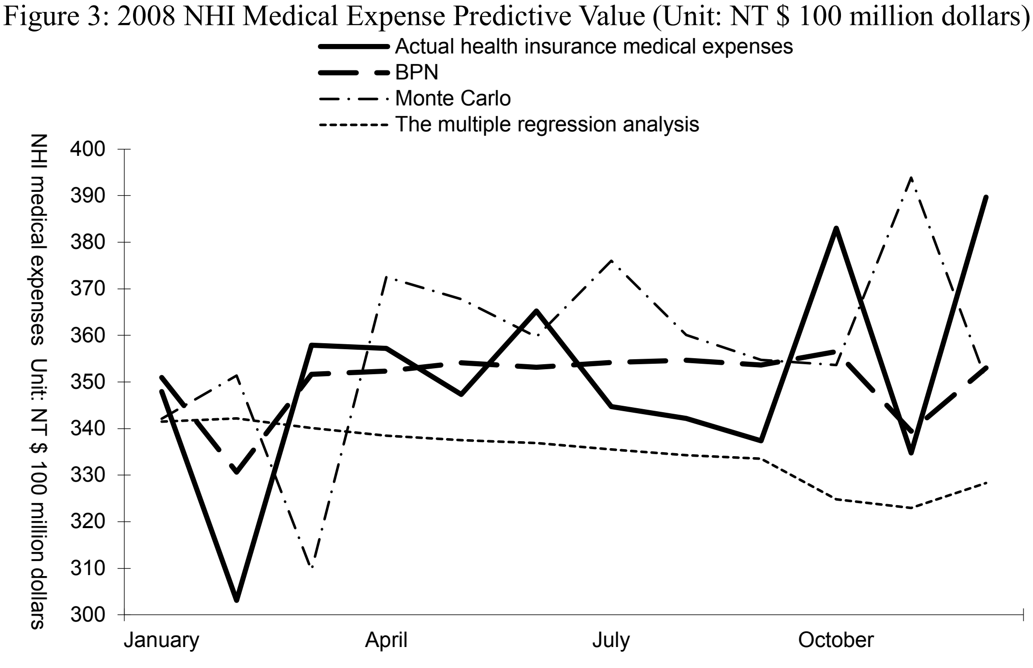
Table 4 shows that using BPN, Monte Carlo and multiple regression it is possible to estimate the NHI medical expenses value for 2008. Figure 3 shows differences between the three prediction models. The real expenditure measures two performance indicators to achieve the best evaluation of the NHI expenditure model. Table 5 shows the actual medical expenditure and the related coefficients of the predictive results from the three models. The strength of correlation, in descending order, between the three predictive models and the actual medical expenditure is: BPN, the multiple regression analysis and Monte Carlo. The results show that the BPN has the best performance indicator, followed by multiple regression and Monte Carlo.

Table 3 Monte Carlo Simulation and Performance Indicators from 2008 (Unit: NT$100 million dollars)

Month	Actual Value	The Predictive Value of Different Simulation Times					
	Actual Health Insurance Medical Expenses	50 Times	100 Times	250 Times	500 Times	750 Times	1,000 Times
January	347.91	348.03	333.77	342.88	345.02	342.07	346.17
February	303.08	352.75	346.52	351.17	358.13	351.35	356.49
March	357.89	303.54	312.35	307.46	311.57	309.58	306.97
April	357.17	364.10	367.52	376.83	366.83	372.52	364.57
May	347.35	347.10	383.98	370.15	367.49	367.78	361.63
June	365.20	378.40	364.75	357.05	352.95	359.70	355.52
July	344.70	376.51	378.66	373.51	386.92	376.01	382.75
August	342.19	363.16	378.17	357.60	353.65	360.10	356.37
September	337.34	364.924	362.83	356.11	359.10	354.70	358.60
October	382.98	342.57	340.79	346.17	346.69	353.66	349.31
November	334.74	407.21	393.05	405.67	398.73	393.83	398.66
December	389.68	349.09	356.74	344.02	343.34	350.48	346.25
MAPE		8.616	9.125	8.888	8.861	8.135	8.475
TIC		0.052	0.05	0.051	0.051	0.046	0.05

We use monthly data from 1996 to 2007 to establish the predictive model, 2008 was used as the forecast evaluation period. Monte Carlo Simulations used different frequencies to predict the most suitable result. Following the simulation 750 times the errors have a smaller MAPE equal to 8.135, and the TIC is equal to 0.046. Therefore, NHI expenditure assessment results of Monte Carlo are compared with other models in this study. The result of the Monte Carlo Simulation is the assessment of the NHI expenditure model.

Figure 3: 2008 NHI Medical Expense Predictive Value (Unit: NT $ 100 million dollars)



Source: the present study.

In this study, three models were used to predict the results of a pair-wise comparison (see Table 6, Panel A), and establish the null hypothesis whether there are differences in the predictive medical expenditure under different predictive models. Based on the results of Table 6, under different predictive models, the F-value of the sample observation was 8.208, reaching 1% significance, and thus the null hypothesis was rejected. This implies that different prediction models used to predict the health care treatment and medical expenses display significant differences. The pair-wise comparison shows the BPN forecast of NHI expenditure (average of 350.35) was significantly higher than the multiple regression forecast (average equal to 334.65). In addition, using the Monte Carlo Simulation to forecast NHI expenditure (average equal to 357.65) was significantly higher than the multiple regression (average 334.65).

Table 4: 2008 NHI Medical Expense Predictive Value and Performance Indicators (NT $ 100 million)

Month	Actual Value	Predictive Value		
	Actual Health Insurance Medical Expenses	**BPN**	**Monte Carlo**	**The Multiple Regression Analysis**
January	347.91	350.96	342.07	341.47
February	303.08	330.64	351.35	342.14
March	357.89	351.65	309.58	340.10
April	357.17	352.35	372.52	338.44
May	347.35	354.08	367.78	337.47
June	365.20	353.16	359.70	336.85
July	344.70	354.18	376.01	335.50
August	342.19	354.64	360.10	334.30
September	337.34	353.64	354.70	333.49
October	382.98	356.51	353.66	324.80
November	334.74	339.41	393.83	322.93
December	389.68	353.02	350.48	328.33
	MAPE	3.936	8.135	6.345
	TIC	0.025	0.046	0.043

Monthly data from 1996 to 2007 was used to establish a predictive model, using 2008 as a forecast evaluation period. When MAPE is closer to zero, it means the measure of the predictive model is better. A small TIC is a small predictive error and the predictive ability is good. The results of the model error compared: BPN error value is minimum, multiple regression error values centered, Monte Carlo prediction error is high.

Next, actual expenditures are further divided in two categories. Those above the mean value shown in Table 6 Panel B and those below the mean value shown in Table 6, Panel C. A difference analysis of the two categories are conducted. In the difference analysis of those above the mean value, the prediction of the three models is significantly lower than the substantive health insurance medical expenses. The BPN is closer to the substantive health insurance medical expenses value. The difference analysis below average, BPN, Monte Carlo forecast substantive health care spending is significantly higher than the substantive health insurance medical expenses. However, the closest substantive health insurance medical expenses, the multiple regression value, is not significant. Therefore, each model used for estimating the actual health insurance medical expenses still has some errors when the prediction is higher (or lower) than the mean value of the actual medical expenditure, so the BPN and Monte Carlo have significantly lower (or higher) predictive results.

Table 5: The Correlation Coefficient of NHI Expenditure Prediction Models

	Actual Health Insurance Medical Expenses	BPN	Monte Carlo	the Multiple Regression Analysis
Actual health insurance medical expenses	1	0.722**	-0.192	-0.415
BPN	0.722**	1	-0.143	-0.122
Monte Carlo	-0.192	-0.143	1	-0.455
The multiple regression analysis	-0.415	-0.122	-0.455	1

*** significance level of 0.01 (two-tailed), significant correlation. But the absolute value of the Monte Carlo correlation coefficient was found to be below 0.4, so it had a low correlation. The multiple regression analysis had a medium correlation as its absolute value was between 0.4 and 0.7. The BPN had a high correlation since its absolute value was above 0.7.*

This study suggests that (1) if MAPE and TIC indicators are used to evaluate the NHI expenditure model, the BPN will produce better results. (2) If the difference analysis is used to predict health insurance medical expenses, the prediction ability of the BPN and Monte Carlo Simulation is better than multiple regressions.

But, when predicting actual medical expenditures, the prediction of the three predictive models all leaned toward the actual expenditures' mean value, which shows they are relatively conservative predictive models. Table 6 shows pair wise comparisons of the prediction models.

Table 6: The Prediction Model Difference Comparison (Unit: NT $ 100 million)

Panel A: Pairwise Comparison			
Model A	Model B	Mean difference	t-value
BPN (Mean =350.358)	Monte Carlo (Mean =357.654)	-7.296	(-1.154)
BPN (Mean =350.358)	Multiple regression (Mean =334.657)	15.701	(5.539) ***
Monte Carlo (Mean =357.654)	Multiple regression (Mean =334.657)	22.997	(3.705) ***
Panel B: Pairwise Comparison for Above Average Health Care Expenses			
Model A	Model B	Mean difference	t-value
Actual health insurance medical expenses (Mean =366.810)	BPN (Mean =352.9455)	13.864	(2.078) **
Actual health insurance medical expenses (Mean =366.810)	Monte Carlo (Mean =348.007)	18.803	(1.715) *
Actual health insurance medical expenses (Mean =366.810)	Multiple regression (Mean =335.002)	31.808	(4.427) ***
Panel C: Pairwise Comparison for Below Average Health Care Expenses			
Model A	Model B	Mean difference	t-value
Actual health insurance medical expenses (Mean =334.904)	BPN (Mean =347.7705)	-12.867	(-1.639) *
Actual health insurance medical expenses (Mean =334.904)	Monte Carlo (Mean =367.301)	-32.397	(-3.502) ***
Actual health insurance medical expenses (Mean =334.904)	Multiple regression (Mean =334.311)	0.592	(0.083)

*This table is based on the estimated average. ***, **, and * indicate significance at the 1, 5 and 10 percent levels respectively.*

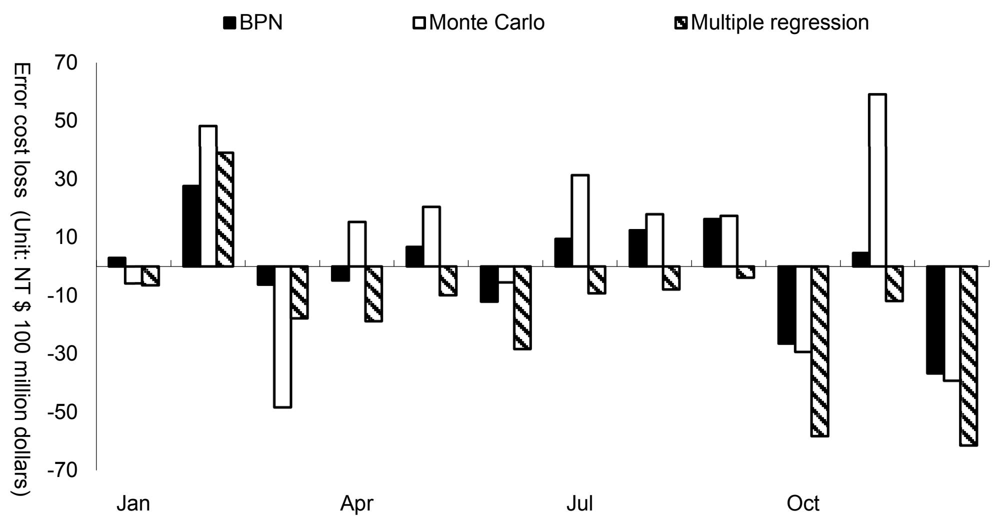
<u>Comparison of Prediction Error Cost</u>

The above analysis deals only with the accuracy of the predictive methods and does not discuss the degree to which the predictions exceed or fall short of the actual medical expenditure. As a result, the possible impact of related costs may be overlooked. Therefore, other than predicting the plus-minus deviation between the prediction and the actual expenditure, opportunity cost A and resource cost B should also be taken into account. Prediction error values of the above three models are substituted into equation (6) to obtain the data for each model on lost cost data, presented in Figure 4 and Table 7. Figure 4 shows the prediction errors of these three models are higher in February, October and December. The prediction errors for the Monte Carlo Simulation in March, July and November are twice as high as the other models. Overall prediction error, opportunity cost A adds resource cost B, from high to low: Monte Carlo Simulation, (NT$ 337.91 hundred million dollars), multiple regression (NT$272.53 hundred million dollars), and BPN (NT$166.485 dollars). From Table 7, the loss cost is calculated for each model: (1) the difference between the Monte Carlo Simulation and multiple regression is $(209.737A + 128.173) - (39.065A + 233.465B) = 170.672A - 105.292B$; (2) For BPN and multiple regression, the difference is $(80.251A + 86.234B) - (39.065A + 233.465B) = 41.186A - 147.231B$ and (3) The difference of cost loss for Monte Carlo Simulation and BPN is $(209.737A + 128.173B) - (80.251A + 86.234B) = 129.486A + 41.939B$.

The models are compared with each other. The differences in the cost loss of the Monte Carlo Simulation and the multiple regression is $170.62A - 105.292B$. That is when $A > 0.617B$, the predictive ability of multiple regression is superior. If $A < 0.617B$, Monte Carlo model has better predictability. The BPN and multiple regression difference is $41.186A - 147.231B$. That is, when $A > 3.575B$, the predictive ability of the multiple regression is superior. If $A < 3.575B$, the predictive ability of BPN is better. For the Monte Carlo Simulation and BPN, the difference is $129.486A + 41.939B$. That is, when $A > 0.324B$, the predictive ability of the BPN is superior. If $A < 0.324B$, Monte Carlo model prediction is better.

Comparing the three models with one another: when the opportunity cost is more than 3.575 times the resource cost, that is $A > 3.575B$, multiple regression is best, followed by the BPN; the Monte Carlo Simulation prediction is poor. If the lost opportunity cost caused by the overestimation is $0.617B < A < 3.575B$, that is, when the opportunity cost is between 3.575 times and 0.617 times the resource cost, the BPN is better than multiple regression, rather than the Monte Carlo Simulation. When the opportunity cost is between 0.617 times and 0.324 times the resource cost, that is $0.324B < A < 0.617B$, BPN is also the best, followed by multiple regression; the Monte Carlo prediction is poor. When the opportunity cost is less than 0.324 times resource cost, that is $A < 0.324B$, then Monte Carlo is the best, followed by the BPN, and the multiple regression is poor. This study provides the relevant units to predict the direction of another application and thinking regarding health insurance medical expenses.

Figure 4: 2008 NHI Expenditure Forecast Model Error Cost Loss (Unit: NT$ 100 million dollars)



Source: the present study

CONCLUSION

This study, using the BPN, Monte Carlo Simulation and multiple regression models evaluated NHI medical expenses in Taiwan, and compared these performance indicators to measure prediction errors of evaluation models. The results show the BPN model is best in the performance indicators. The NHI expenditure prediction of the BPN had the best predictive power. The NHI expenditure error was relatively small. Therefore, this study suggests that using the BPN to assess NHI expenditure is better and the result is consistent with those of most prediction-related literature, e.g., Zou et al. (2007), Huang (2008) and Yeh (2009).

Table 7: 2008 annual forecast model error cost loss comparison table (Unit: NT $ 100 million dollars)

Model╲Mon.	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Error Cost loss
BPN	3.049	27.561	-6.242	-4.821	6.731	-12.031	9.483	12.441	16.301	-26.472	4.679	-36.661	80.251A+86.234B
Monte Carlo	-5.840	48.272	-48.301	15.354	20.421	-5.499	31.304	17.912	17.361	-29.320	59.095	-39.191	209.74A+128.17B
Multiple regression	-6.441	39.065	-17.789	-18.728	-9.879	-28.351	-9.198	-7.889	-3.847	-58.188	-11.805	-61.352	39.065A+233.46B

Source: the present study. Explanation: When the forecast overestimated one unit will generate opportunity costs "1A" times; when the forecast underestimated one unit will generate a resource cost "1B" times. Refer to Equation (6) the two add up the cost, that is, the model prediction error due to the costs incurred.

If taking into account lost opportunity costs when the forecasting model overestimates the expenditure and resource cost that will occur when the model underestimates the expenditure the Montel Carlo Simulation prediction may be superior to the BPN and multiple regression. This result is the same as Shing-Hwang et al. (2009), who stated that prediction ability of multiple regression is less than the Monte Carlo Simulation model. Real et al. (2008) stated that predictive ability of the neural network is not as good as that of the multiple regression. The main reason is when different mechanisms of risk factors are reconsidered, equilibrium conditions will be altered and thus lead to different results.

Table 8: Models in Predictive Power Comparison Table

Condition	Predictive power
$\frac{\text{Opportunity cost}}{\text{Resource cost}} > 3.575$	Multiple regression $\succ$ BPN
$\frac{\text{Opportunity cost}}{\text{Resource cost}} > 0.617$	Multiple regression $\succ$ Monte Carlo
$\frac{\text{Opportunity cost}}{\text{Resource cost}} > 0.324$	BPN $\succ$ Monte Carlo
$\frac{\text{Opportunity cost}}{\text{Resource cost}} > 3.575$	Multiple regression $\succ$ BPN $\succ$ Monte Carlo
$0.617 < \frac{\text{Opportunity cost}}{\text{Resource cost}} < 3.575$	BPN $\succ$ Monte Carlo $\succ$ Multiple regression
$0.324 < \frac{\text{Opportunity cost}}{\text{Resource cost}} < 0.617$	BPN $\succ$ Multiple regression $\succ$ Monte Carlo
$\frac{\text{Opportunity cost}}{\text{Resource cost}} < 0.324$	Monte Carlo $\succ$ BPN $\succ$ Multiple regression

In Table 8, values of cost loss are computed based on the values of error cost obtained from each model. Then, costs ranging from different conditions are organized into Table 8.

The relevant assessment indicators of the Monte Carlo Simulation method used in this study are relatively poor. However when the resource cost is more than 3.70 times (1/0.27) to the opportunity cost the Monte Carlo Simulation is the best forecasting method, second is the BPN and the multiple regression is last. The result is different from Huang (2008), but the prediction of the Monte Carlo Simulation has its advantages. This prediction model has desirability and comparability. The analyses in this study shows that Monte Carlo Simulation has better predictive capacity than multiple regression analysis. Chiu et al. (2006), and Qing and Parry (2009) also believed that Monte Carlo could be used as a comparative method. This study suggests that different prediction models have different advantages according to different conditions.

The study used the BPN to determine the relevant input variables. Results show there are three factors that have an impact on NHI medical expenses. These are the aging population index, the inflation rate and the number of the insured population.

The aged population in Taiwan has been increasing. Hitiris and Posnett, 1992; Murthy and Ukpolo, 1994 and Herwartz and Teilen, 2003 all confirmed the aging of the population is directly proportional to health care expenditure. Therefore, as there is a higher aged population in Taiwan, the need for treatment of long term chronic diseases and the medical resources required by the elderly increases relatively. Medical resources may even be wasted. The study considered the aging population impacts health insurance medical expenses.

When inflation rises, health insurance expenditure on hospital equipment increase. Drug costs also increase. Gerdtham et al., 1992 and Karatzas, 2000 found that NHI medical expenses vary depending on inflationary pressures. We found the inflation rate is the second leading cause of health care expenditure.
Finally, this study shows the size of the insured population is related to the usage of health insurance medical resources. Xie et al. (1998), Chi et al. (2001), and Su et al (2003) all argue that one of the main variables affecting health insurance medical expenses is the size of the insured population. Due to the increase in the

numbers insured, the impact insured medical expenses is an inevitable phenomenon. In summary, this study suggests that implementation of a health insurance policy should be based on the aging population index, inflation rate, and size of the insured population.

The results are performance indicators to measure the predictive ability of the models. The BPN, has better and more consistent prediction results. In addition, the conditional results obtained when resource cost and opportunity cost were taken into account are inconsistent with those of other literature. BPN is not the best predictive method under all cost conditions. Other prediction models using different cost conditions may be better than the BPN. The greatest contribution of the study is to provide relevant government units with information when implementing policy.

Due to time and data constraints, this study only selected historical data from 1996 to 2008. Future research might increase the time period and the type of data. This would improve generality of the model. In fugure research consideration can be given to increasing the importance political and economic variables. In this study, financial and economic data were used as variables. External environmental factors were not considered. Economic prosperity, social conditions, political environment, etc., change over time and can be a factor affecting the NHI. Considering these variables will allow a more complete estimate. Future researcher can use this methodology for other forecasting in other industries.

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