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# The Application of Artificial Neural Network Method to Investigate the Effect of Unemployment on Tax Evasion

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## Abstract

Although tax is an important component of government revenue which is used to finance government expenditures, there are many causes that lead people to avoid or evade from paying tax such as low income of taxpayers, high tax burdens; increase the size of government, trade openness, high inflation and unemployment. This study postulates that unemployment has a high effect on tax evasion. The present study applied the Sensivity Analysis with Artificial Neural Network (ANN) methodology to investigate the effect of unemployment on tax evasion and also to determine the relative importance of unemployment among other causes of tax evasion for Malaysian data from 1963-2012. Results reveal that there is a positive relationship between unemployment and the extent of tax evasion, and unemployment has a high effect on tax evasion among other causes of tax evasion.

**Keywords:** Tax Evasion; Artificial Neural Network Method; Sensitivity Analysis.

## 1. Introduction

Tax is an important component of government revenue which is used to finance government expenditures. There are many reasons that cause the amount of tax collected to be lower than expected, and one of them is tax evasion. When the taxation system is ineffective, many people will exploit the ineffectiveness to avoid paying tax, resulting in the popularity of tax evasion. Tax evasion is defined as "intentional illegal behavior or activities involving a direct violation of tax law to evade the payment of tax" (Richardson, 2008).

Tax evasion can arise because of several factors such as high tax burdens, high inflation, low income of taxpayers, increase in the size of government, limited trade openness, a lack of tax culture, complicated tax structure and many other factors[1]. The other factor that may strongly lead to tax evasion is unemployment. Many researchers such as Dell'Anno (2007) and Sameti et al. (2009) have shown that unemployment is the main cause of shadow economy. Regarding the relationship between shadow activities and hiding earned incomes for the purpose of tax evasion; unemployment can also strongly lead to the increase of tax evasion. High unemployment leads people to find jobs in the informal economy, resulting in the increase of illegal activities which will correspondingly also result in the increase the level of tax evasion.

Among the large number of studies related to tax evasion for developed and developing countries, several of these studies have investigated the phenomenon of tax evasion in Malaysia. Nevertheless, there is clearly a dearth of study that investigated the effect of unemployment on tax evasion. To the best of our knowledge, among the large number of studies related to tax evasion; to date, there has been no study that investigated the effect of unemployment on tax evasion and additionally, there is also no study that has applied the Sensitivity Analysis Artificial Neural Network

[1] - For more details, refer to Cebula and Saadatmand (2005), Bayer and Sutter (2008) , Busato et al. (2010), Fishburn (1981), Crane and Norzad (1986), Fishlow and Friedman (1994), Caballe and Panade (2004), Embaye (2007).

(ANN) method to determine the relative importance of each variable on tax evasion in Malaysia. Therefore, this study attempts to fill these gaps and will apply the Sensitivity Analysis with ANN method to investigate the effect of unemployment on tax evasion and to determine the relative importance of unemployment on tax evasion among other causes of tax evasion on Malaysian data during 1963-2012.

This study is organized as follows. The following section presents a brief review of the literature related to tax evasion. The next section then explains the methodology used while the final remaining sections present the results and conclusions of this study.

## 2. Literature Review

In literature, there are many causes that lead to tax evasion. Past studies have identified many factors that lead to the extent of tax evasion such as tax burdens, tax culture, complicated tax structure, inflation rate, income of the taxpayers, the size of government and regulations, trade openness and many other factors. Cebula and Saadatmand (2005), Bayer and Sutter (2008) and Busato et al. (2010) showed that high tax rate and the excess burdens of tax lead to higher tax evasion. To investigate the effect of the inflation rate on tax evasion researchers have shown that the inflation rate has a positive effect on tax evasion[2]. Tax evasion is also affected by changes in the income of the taxpayers. Embaye (2007) showed that there is a positive relationship between income of the taxpayers and tax evasion. The size of the government and the intensity of regulations are other causes that lead to tax evasion. Many researchers such as Dell'Anno (2003) and Sameti et al. (2009) showed that the size of the government and high intensity of regulation promote shadow economy. It is clear that more shadow economy lead to higher level of tax evasion. Jain (1987) in his study which investigated other causes of tax evasion found that complicated tax structure, dishonest tax officials and high tax rates (especially high tax rate on sales) are factors that cause high black money in India. Another factor that may strongly affect on tax evasion is unemployment rate. Sameti et al. (2009) and Dell'Anno (2007) found that there is a positive relationship between the unemployment rate and shadow economy.

There are various studies related to tax evasion for developed and developing countries, several number of these studies have investigated the phenomenon of tax evasion for Malaysia. In this regard, we can point to the study of Kasipillai et al. (2000), Kasipillai et al. (2003), Fatt and Ling (2008), Jaffar Harun et al. (2011) and Miskam et al. (2013) that investigated several aspects of tax evasion in Malaysia, but there is no study which investigated the effect of unemployment and the importance of each variable on tax evasion. It should be noted that there is no study that applied Artificial Neural Network method to determine the importance of each variable on tax evasion. Hence, this study attempts to fill these gaps on the impact of unemployment on tax evasion by investigating into the relationship between unemployment and tax evasion and also to determine the importance of unemployment among other causes of tax evasion in Malaysia. To achieve these aims, the Sensitivity Analysis with Artificial Neural Network method is applied on Malaysian data during 1963-2012 to determine the importance of independent variables.

## 3. Methodology

Among the various studies that used the econometric methods to investigate the relationship between macroeconomic variables and tax evasion, none have attempted to determine the importance of each variable on tax evasion[3]. In this study, the Artificial Neural Network method (ANN) is employed to investigate the relationship between unemployment and tax evasion and to determine the importance of each variable on tax evasion.

Numerous researchers have used the ANN method in the area of economics. Kohzadi et al. (1995) compared the Neural Network model and the ARIMA model to forecast the price of corn during 1974-1993. The results reveal that the ANN method is more accurate than ARIMA model (in their study). Zarra Nezhad et al. (2009) forecast the exchange rate by applying the ANN method during 2006 to 2009; they also compared the ANN method and the ARIMA model. Their results indicate that the ANN presents a better estimation than the ARIMA model. Similar results were seen in the study by Gademe and Moshiri (2002) which applied the neural network method to forecast economic growth of Iran's economy. They compared the Autoregressive model and neural network method and concluded that the network method was precise as well as the Autoregressive model for forecasting time series data.

Many studies have applied the Neural Network method for modeling macroeconomic variables; however, none of them have investigated the area of tax evasion. To fill this gap, this study employs the Sensitivity Analysis method with Neural Network method to investigate the effect of unemployment on tax evasion and determine the importance of unemployment on tax evasion by using Malaysian data from 1963-2012.

[2] - Fishburn (1981), Crane and Norzad (1986), Fishlow and Friedman (1994), Caballe and Panade (2004).

[3] - The most popular of the econometric methods are OLS, 2SLS, 3SLS, VAR, ARMA, ARIMA, GARCH, and ARCH.

### 3.1. Artificial Neural Network Method

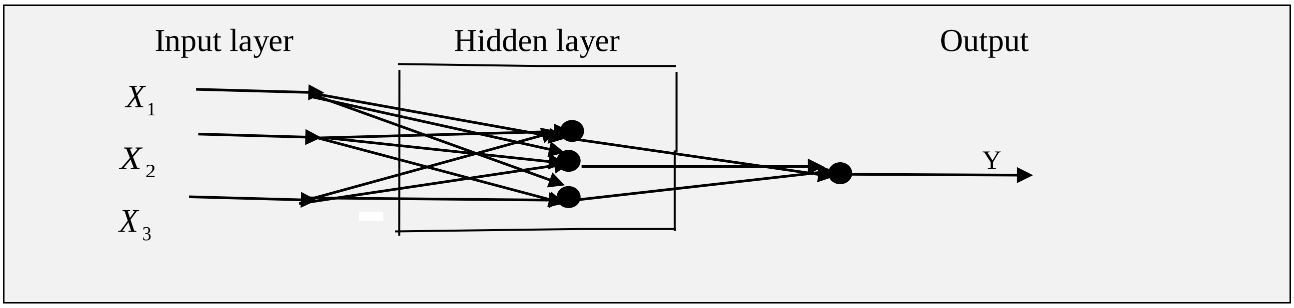
The simplest model of an Artificial Neural Network is the binary threshold model of McCulloch and Pitts (1943) as follows[4]:

$$Y = g(\sum_{j=1}^{j} \beta_j X_j - \mu) \tag{1}$$

$$g(u) = \begin{cases} 1 & \text{if } u \geq 0 \\ 0 & \text{if } u < 0 \end{cases}$$

where Y is the output variable and $X_j$, j = 1... J is the input variables, β is the synaptic weight of each input$X_j$, g (u) is the activation function, and μ is threshold. Each extension model of the Neural Network includes the input layer, output layer and hidden layer(s). Figure (1) shows an example of a multilayer perceptron (MLP) with a single hidden layer.

**Figure 1: Multilayer Perceptron (MLP) with a Single Hidden Layer**




The relationship between the input and output is determined by the weighting (β); therefore, the net value of the output neurons is as follows:

$$NET_t = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 = \beta_0 + \sum_{j=1}^{6} \beta_j X_j \tag{2}$$

As mentioned above, the extensions model of the binary threshold is the introduction of a hidden layer between the input layer and the output layer.

$$Y = h(\sum_{k=1}^{K} \alpha_k g(\beta_k' X)) \tag{3}$$

$$\beta_k = [\beta_{k1}, \beta_{k2}, ..., \beta_{kJ})]' \quad ; \quad X = [X_1, X_2, ...X_J]'$$

Where h (u) is another nonlinear activation function. In this case, the inputs are connected to the hidden layer and weighted at each hidden layer transformed by the activation function g. Data processing for output neurons is done by using the activation function[5]. For a set of inputs and outputs $\{X_t, Y_t\}$, MLP estimates the parameters of the MLP network by minimizing the sum of the squared deviations between the output and the network.

$$\sum_t [Y_t - \sum_k \alpha_k g(\beta_k' X)]^2 \tag{4}$$

Application of the Neural Network method involves several steps; the main steps include normalization of data, building the network, determining the ratio of training and testing samples, training function, using performance function, training the network and simulation.

[4] - For more details, refer to Campbell et al. (1997).
[5] - Among the many linear and nonlinear activation functions in the Neural Network method, the most popular ones are the logistic cumulative distribution function and hyperbolic tangent.

Data normalization is often performed before the training process begins to avoid computational problems[6]. The second step in using the ANN method is building the network. There are two kinds of Artificial Neural Network model which are the Feed-Forward neural network or static network and the feedback neural network or dynamic network[7]. Dynamic networks are similar to the lag variables in the regression model where output not only depends on inputs, but is also a function of the inputs of the previous period[8]. In other classifications of artificial neural networks, the most popular of the artificial neural networks are the Multilayer Perceptrons (MLP) and the Radial Basis Function (RBF) network. The most popular ANN for using nonlinear time series data is MLP. MLP with the nonlinear activation functions in the hidden layer and sufficient number of neurons in the hidden layer as well as linear activation functions in the output layer is capable of estimating each function with minimum error. Determining the training and testing sample is required for training the ANN. The training sample is used for the development of the ANN model and the test sample is adopted to evaluate the estimating and forecasting ability of the model[9].

Choosing the activation function is another step in the application of the ANN method. Data processing for output neurons is done by using the activation function. Among the many linear and nonlinear activation functions, the most popular nonlinear activation functions are the logistic cumulative distribution function and the hyperbolic tangent that are defined respectively as follows[10]: .

$$g(u)=\frac{1}{1+e^{-u}} \quad ; \quad g(u)=\frac{(e^{u}-e^{-u})}{(e^{u}+e^{-u})} \qquad \textbf{(5)}$$

Another step in the ANN method is using the performance functions to minimize the errors of the estimated equation. The most popular criteria among several criteria to minimize the estimated errors are as follows[11]:

1-Mean Squared Error or Root Mean Squared Error.

$$MSE=\frac{\sum(\hat{y}_t-y_t)^2}{n} \quad ; \quad RMSE=\sqrt{\frac{\sum(\hat{y}_t-y_t)^2}{n}}$$

2- Mean Absolute Deviation or Mean Absolute Percentage Error. (MAD, MAPE)

$$MAD=\frac{\sum|\hat{y}_t-y_t|}{n} \quad ; \quad MAPE=\frac{\sum\left|\frac{\hat{y}_t-y_t}{y_t}\right|}{n}$$

3-Theil’s U Statistic.

$$U=\frac{\sqrt{\frac{\sum(\hat{y}_t-y_t)^2}{n}}}{\sqrt{\frac{\sum(\hat{y}_t)^2}{n}}+\sqrt{\frac{\sum(y_t)^2}{n}}}$$

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6 - For more details, refer to the study of Lapedes and Farber (1987).

7 - In a static network, data moves only in one direction to forwards. In a dynamic network, there is a loop direction from the vectors in the hidden layer to the input layer.

8 - Dynamic network is precisely more than feed-forward neural network for time series data.

9 - For more details related to the selection of the training and testing sample of the network, refer to the study of Weigend et al. (1992).

10 - The value of the logistic cumulative distribution function is between 0 and 1, and the value of the hyperbolic tangent is between -1 and 1. For more details, refer to Campbell et al. (1997), and Gademe and Moshiri (2003).

11 - For more explanation and definition of each criteria, refer to the study of Hoiden et al. (1990).

### 3.2. Importance Analysis with ANNs

The "black box" feature of ANN causes to difficulty in evaluating the relative importance (RI) of input variables to output variables. There are two different possible solutions here. The first is the connection weights explicit computation between neurons (e.g., Garson, 1991; Yoon et al., 1994 and Tsaur et al., 2002). Howes and Crook (1999) criticized Garson's model by indicating that it does not involve the bias effect. Yoon's approach could lead to weight cancellation and hence cause a zero denominator. Nevertheless, these methods are reliable in real applications. In a latest study, Wong et al. (2011a) analyzed the above three approaches in calculating the significance of determinant factors to the supply chain operation performance. He observed that Tsaur's approach produces different factor rankings compared to Garson's and Yoon's approaches. The second method demonstrates by a comparison of before-and-after of the output variations after the adjustment or remove of the input variables. The change of mean square error technique (COE) Sung (1998) and sensitivity analysis method are the two most well-liked approaches in the second group (Olden and Jackson (2002), Özesmi and Özesmi (1999)). The COE method calculates the change of MSE right after removing the input variable from the original ANN. This method is similar to the stepwise method for identifying independent variables in multiple linear regression. COE has been employed to the analysis of several industrial engineering problems (Sung (1998), Wong et al. (2011a), Wong et al. (2011b), and Wong et al. (2012)) with favourable results. Also, sensitivity analysis method works by varying every input variable over either the full or a partial range of possible values whilst holding rest of the input variables unchanged at a specified percentile, so that the relative importance of variables of interest can be evaluated by the induced variation from output variables. Sung (1998) compared sensitivity analysis and COE in a real engineering problem, and discovered that both approaches produced comparable results. So far, primevigilance of any of mentioned models to other has not been established Gevrey et al. (2003) and Olden et al. (2004).

### 3.3. Model Estimation

Incorporating theoretical and empirical studies, tax evasion can be written as a function as follows:

$$TE = f(TB, G, Y, \pi, UN, OP)$$

TE is tax evasion. Tax evasion is a latent variable (unobserved variable), as there is no data for tax evasion (during the period under survey); therefore, this study considers the ratio of C to M2 as a proxy of tax evasion. C/M2 is the ratio of currency to liquidity. (A similar proxy has been used by Tanzi (1982) and Embaye (2007)). Input variables to model estimations are $TB, G, Y, \pi, UN, OP$. TB is tax burden, G is the size of government, π is the inflation rate, OP is trade openness, Y is income of the taxpayer and UN is the unemployment rate. The description of each variable used in this study is presented in Table (1)[12].

**Table 1: The Description of Variables**

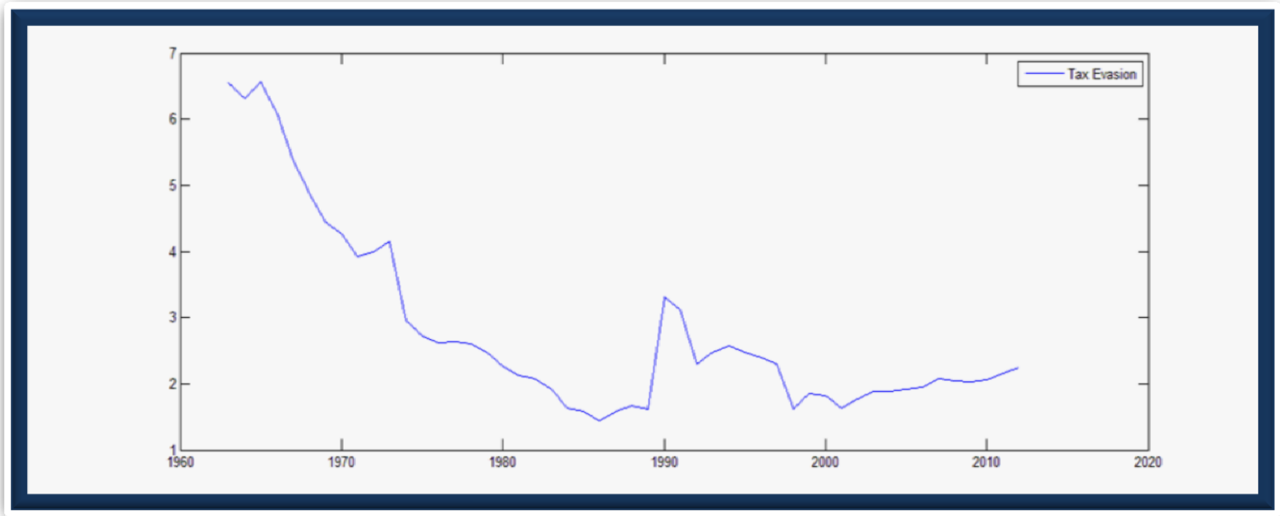
| Variables | Descriptions |
|---|---|
| TB | The tax burden is calculated as the ratio of tax revenue to GDP (constant 2000 US$) |
| G | The size of government is calculated as the ratio of government consumption (constant 2000 US$) to GDP (constant 2000 US$) |
| Y | A measure of the income of taxpayer (GDP per capita ) calculated as GDP (constant 2000 US $) divided by population. |
| $\pi$ | Percentage Change in consumer price index |
| UN | Growth of unemployment |
| OP | The ratio of sum of export (constant 2000 US$) and import (constant 2000 US$) to GDP (constant 2000 US$) |

[12] - All data are collected from the annual Economic Report for the period from 1963-1980 and the World Development Indicators (WDI) during 1980-2011.

## 4. Results

Figure 2 shows the level of tax evasion from 1963 to 2012 in Malaysia. As can be seen, although tax evasion has been fell from 1963 to almost 1989, after 2008 there is a jump in the tax evasion which emphasizes the need for research on this phenomenon.

**Figure 2: The Tax Evasion between 1963 to 2012**




Input variables are divided into two main category: those which have a rising trend in these years (Figure 3) and other inputs which don't have any obvious pattern among these years that can be classified as fluctuated trends (Figure 4).

**Figure 3: Three Rising Trends from 1963 To 2012**

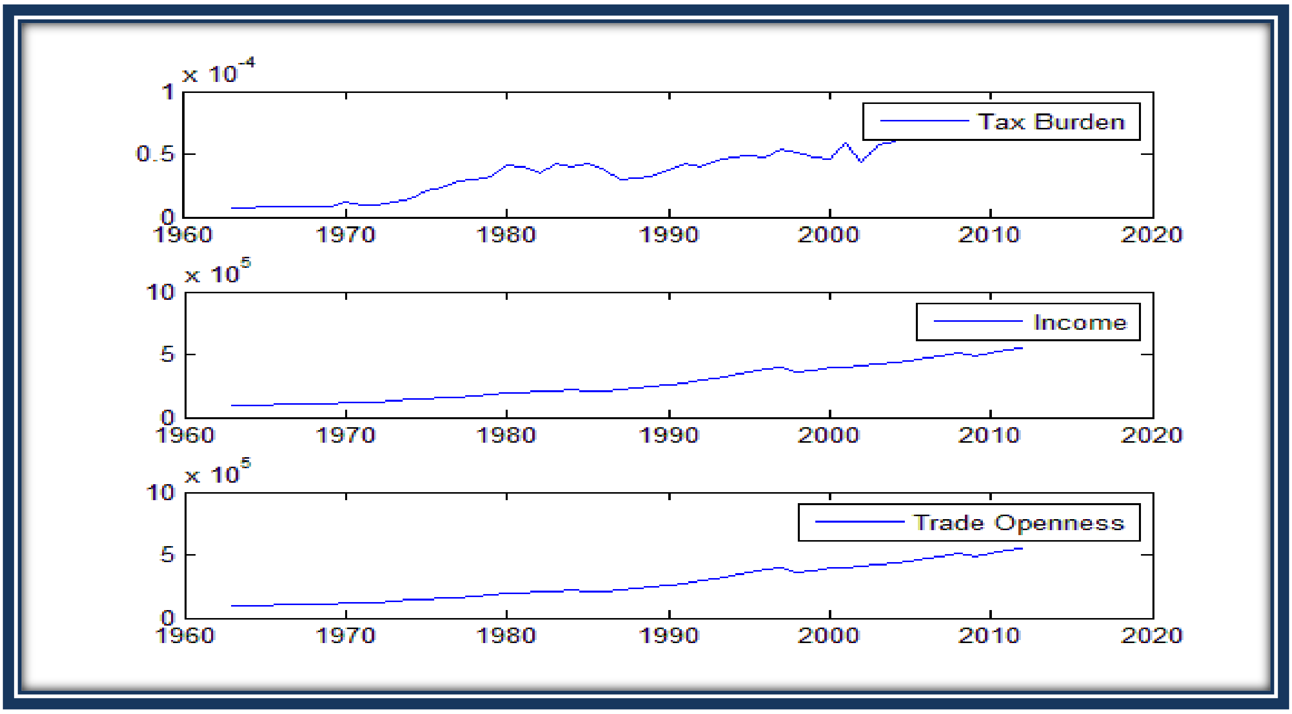
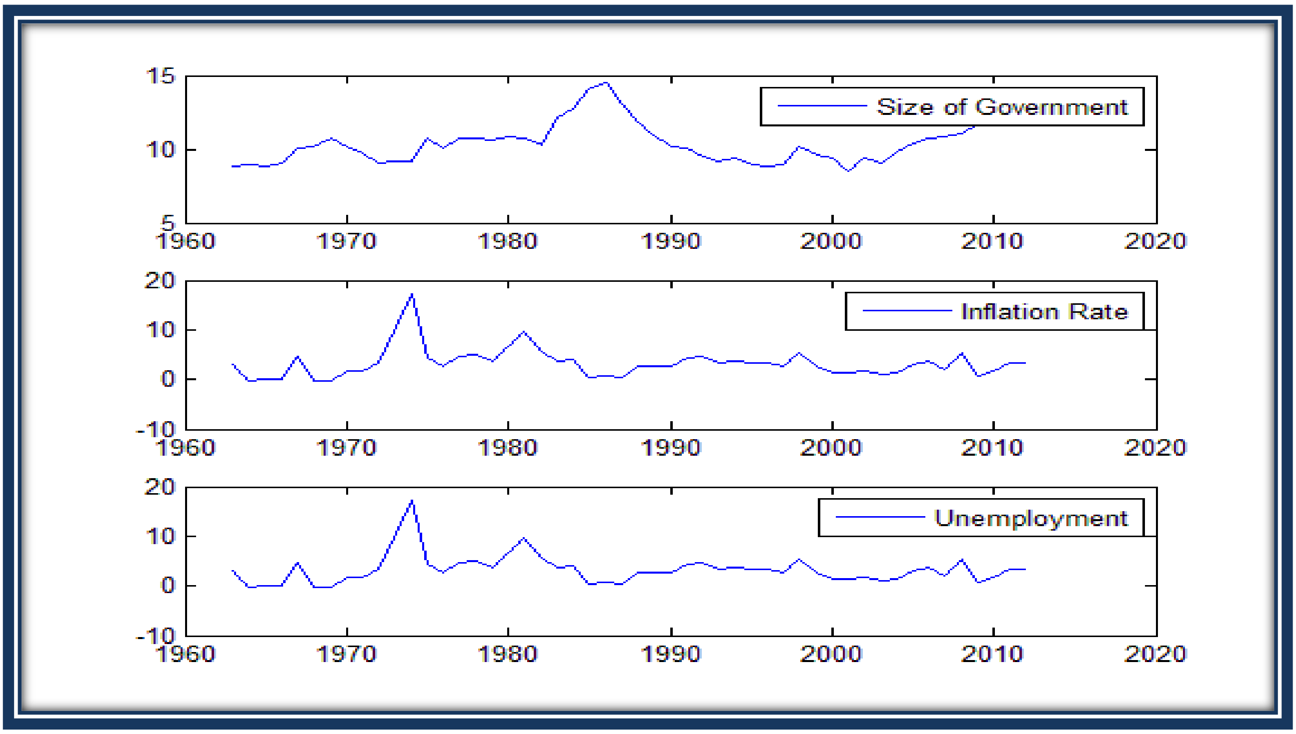


**Figure 4: Three Fluctuated Trends from 1963 To 2012**




As can be seen in above figures; the trends of input variables are not linear; therefore the ANN method is the appropriate method for nonlinear inputs to investigate

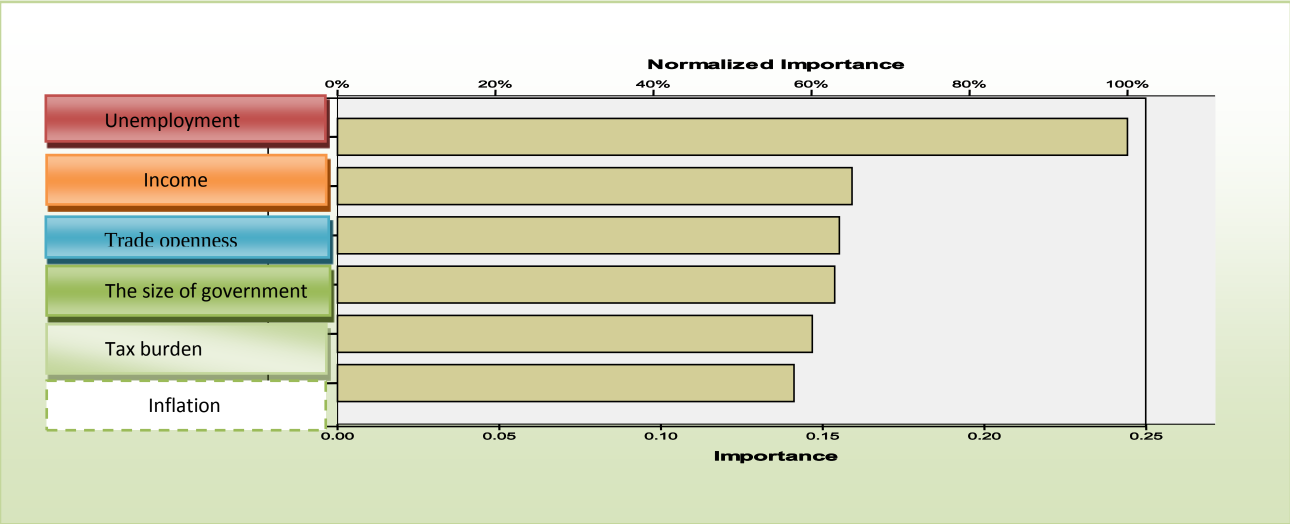
After modeling, normalization of data, building the network, determining 70% of the data for training and 30% for testing, using algorithm iterations to balance the network weights (the error back propagation is the most well-known one) and training the network, the synaptic weights were determined (This was done so that the network is trained to minimize the predicted errors that are measured within the model). The coefficient estimation of a neural network for a nonlinear system is not as easy as linear parameter estimation. There may be several relative optimum answers for minimizing the difference between the real value of output variable and the achieved results from the network. This study applies multilayer perceptron (MLP) with 6 factors for the input layer. The input variables are tax burden, the size of the government, inflation rate, trade openness, income of taxpayers and unemployment. MLP consists of 1 hidden layer with nonlinear activation function. The number of units in the hidden layer is 17, indicating that 17 columns of synaptic weights exist for 70% of the data. In total, each variable has 17 columns weight and 33 rows. The mean of each unit layer for the 33 rows is calculated and then the mean of all layers for each variable is calculated. After calculating the mean of each unit layer and calculating the mean of all layers for each variable, the coefficient estimated by the model is determined as follows:

$$TE = 1.4 * TB + 1.144 * G + 0.78 * \pi - 1.803Y + 1.94 * UN - 1.725 * OP \qquad (6)$$

The Neural Network Model is able to determine the importance of each variable in the best model. Table (2) and Figure (5) show the importance of the input variables on tax evasion in modeling the Neural Network method.

| Table 2: The Importance of Independent Variable | | |
|---|---|---|
| **Variables** | **Importance** | **Normalized Importance** |
| Tax burden | .147 | 60.1% |
| The size of government | .154 | 62.9% |
| Inflation rate | .141 | 57.8% |
| Trade openness | .155 | 63.5% |
| Income of taxpayers | .159 | 65.1% |
| Unemployment rate | .244 | 100.0% |
| Source: The Outputs of Artificial Neural Network Method | | |

**Figure 5: The Normalized Importance of Independent Variable**




Based on the Table 2 and Figure 5, the main causes of tax evasion is unemployment; the normalized importance of this variable is at the highest value among other factors (100%). According to Equation (6), there is a positive relationship between the unemployment rate and tax evasion. This signifies that when unemployment is high, people have high motivation toward shadow activates and find jobs in the informal economy or create self-employment without any licenses for the purpose of evading taxes. When they work in the informal economy, they hide their incomes to avoid paying taxes; therefore, the level of tax evasion will increase.

Another factor that has a high effect on tax evasion is the income of the taxpayer. Based on our results, there is a negative relationship between the income of taxpayer and tax evasion. This signifies that an increase in income leads to a decrease in level of tax evasion. It should be noted that the effect of income on tax evasion in each country is not clear and is an empirical study. There are several reasons to determine the positive or negative relationship between the income of taxpayer and tax evasion. One of these reasons is the marginal utility of income. When the marginal utility of income is high, taxpayers avoid paying tax and tax evasion will increase, but an increase in income and a decline in the marginal utility of income will lead to a reduction in tax evasion. Other reasons that have high effect to determine the positive or negative relationship between the income and tax evasion are fine rate (punishment rate) and probability of detection of taxpayers for those that avoid paying taxes. When fine rate is high, taxpayers prefer to declare their income to avoid pay more money as punishment of evasion and therefore the level of tax evasion will decrease.

The third factor that has a high effect on tax evasion is trade openness. The normalized importance of this variable is relatively high among other independent variables and there is a negative relationship between trade openness and tax evasion. As we know, when the economy is open, export and import is legal and all trades are lawful. When the government performs difficult restrictions for trade, the export and import of goods will occur illegally and will often be smuggled. Since there is no tax on illegal trade, tax revenue will decrease and this will lead to an increase in tax evasion. Therefore, more trade openness leads to a huge reduction in tax evasion.

The fourth important cause of tax evasion with positive effect is the size of the government and the intensity of regulations. We know that when the size of the government increases, the intensity of regulations will increase. An increase in the intensity of regulations leads toward in the informal economy; therefore, tax evasion will increase.

Tax burden and the inflation rate are respectively other causes of tax evasion with positive effect. When tax burden is high, taxpayers try to find a way to evade or avoid paying tax; therefore, tax evasion will increase. The positive relationship between the inflation rate and tax evasion indicates that an increase in the inflation rate leads to the higher level of tax evasion. As we know, high inflation can influence the decision of the taxpayers. When inflation is high, taxpayers prefer to save their money to hold their purchasing power and avoid paying taxes; therefore, resulting in the increase of tax evasion.

## 5. Conclusion and Suggestions

The first purpose of present study was to investigate the effect of unemployment on tax evasion while the second purpose was to determine the relative importance of unemployment among other causes of tax evasion. To achieve these aims, Sensitivity Analysis with the Neural Network method on Malaysian data from 1963-2012 are applied. The network consists of a multilayer perceptron (MLP) with 6 factors for the input layer. The MLP consists of 1 hidden layer with a nonlinear activation function in the hidden layer. The activation function in the hidden layer was the hyperbolic tangent; the number of units in the hidden layer was 17 and the identity activation function was utilized in the output layer. After modeling, training the neural network and choosing the best model with minimum error, we came to the conclusion below. The unemployment rate is the main factor that leads to high tax evasion with a positive effect among other factors. The income of the taxpayer is the second factor that has a high effect on tax evasion; additionally, there is a negative relationship between the income of taxpayer and the extent of tax evasion. The other important factor is trade openness which has a negative effect on tax evasion. The size of the government and the intensity of regulations, tax burden and the inflation rate respectively are other important causes of tax evasion with a positive effect on the extend of tax evasion.

Based on the results of present study, it can be suggested that in order to decrease tax evasion, policy makers should note that high unemployment in the economy may lead people to find jobs in the informal economy and result in an increase of tax evasion. Therefore, policy makers should try to reduce unemployment. Additionally, increasing the income of taxpayers, reducing the rate of tax, decreasing the restriction of law for trade, decreasing the intensity of regulations and controlling inflation are other suggestions that could lead to a decline in the level of tax evasion.

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