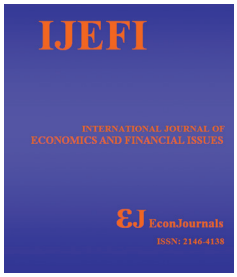

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Modelling and Forecasting Recessions in Oil-exporting Countries: The Case of Iran

Shahram Fattahi[1]*, Kiomars Sohaili[2], Hamed Monkaresi[3], Fatemeh Mehrabi[4]

[1]Razi University, Iran, [2]Razi University, Iran, [3]Razi University, Iran, [4]Razi University, Iran. *Email: sh_fatahi@yahoo.com

ABSTRACT

Business cycles show the ups and downs of the national production and can have a great impact on macroeconomic variables. That is why predicting business cycles in macroeconomic is of great importance. Since the main goal of economists is to provide the ground for economic stabilization and to prevent economic fluctuations and instabilities, knowing that the economy has entered a period of economic expansion or recession can be efficient in determining effective economic policies. In this research, using statistical data during 1974-2014 and decision making tree, we tried to forecast the next recessions in Iran. The results show that, among the indicators used, momentum imports, revenue from oil exports, unexpected momentum inflation (INF), real total import, and INF are more effective in recession forecast. Also, the results indicate that boosted regression trees can be a useful technique for analyzing economic policy.

Keywords: Modelling, Recessions, Oil-exporting, Iran
JEL Classifications: E37, E32, C53, C52

1. INTRODUCTION

After almost a century of the first scientific studies on the business cycles, there are still a lot of controversies over the causes of the emergence and the mechanism of transmission of business cycles. It is because economic planning would not make sense without having an understanding of fluctuations in gross domestic product (GDP), its causes, and origins.

In fact, economy also has certain cycles, as human and nature, which have completely different properties; in a general classification, these business cycles can be divided to periods of economic recession and expansion. Accordingly, predicting these cycles are of particular importance since they reflect national production fluctuations and given that economic situation is completely different due to each cycle's prerequisites so policies and strategies will change depending on the situation. As a business cycle, recession forecast will be very important because economic growth rate is negative during this period and the volume of economic activities decreases.

Thus, this research is an attempt to thoroughly investigate predicted values of the parameters affecting economic recession in Iran with an approach to boosted regression trees (BRT). To do so, the researcher first reviewed the literature and then briefly referred to several foreign and domestic investigations followed by introducing regression trees (BRT) to study indicators and start forecast process. In the end, a report of the research findings will be presented.

2. THEORETICAL FRAMEWORK

Many definitions have been raised for business cycles but almost all have the same meaning. Accordingly, there have been less debates on this issue. Abrishami and Mehrara (2002) defined economic cycle as follows:

"Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than 1 year to 10 or 12 years; they are not

divisible into shorter cycles of similar character with amplitudes approximating their own."

In a similar definition, Dornbush et al. argued that business cycles are regular ups and downs of expansion and recession in economic activities on the path of economic growth. Lucas also descried business cycles as recurrent deviations of real GDP over a long-term trend.

Abrishami and Mehrara (2002) definition is an obvious description of the main features of business cycles. There are three main points in this definition:

These fluctuations in major economic activities are not only related to national production but are also considered important for some other variables, such as employment, price level, and financial market variables.

Business cycles do not belong to certain sectors of economy or a specified number of variables; however, expansion and recession may arise in many economic activities at the same time. This feature is known as "commovment."

Patterns of recession and expansion recur continuously but do not create alternating pattern. This means that expansion and range of fluctuations are not always equal and a sequence of economic recession and expansion have been seen over and over again.

As defined, economic cycles are regular fluctuations in macroeconomic activities of the country. Essentially, it means that every observed fluctuation in the economy does not necessarily reflect an economic cycle. Fluctuations in the economy of a country can random - such as war, strikes, and revolutions - or seasonal. The difference between seasonal and cyclical fluctuations is that the former occurs in certain periods of time (such as increased demand for many goods in the New Year) while certain periods of business cycles cannot be forecasted. Four stages of business cycles can be briefly explained as expansion and recovery, prosperity, recession, and trough or depression (Sayadzadeh and Jamaldikaleh, 2008).

One of the most important questions to be asked in the context of the business cycle, is that what shocks can cause fluctuation in this cycle? One of the views in this regard is that unexpected increase in government spending or a financial crisis can cause shocks in business cycle and this is true to some extent but basically they are not considered as the main source of periodic instability. In fact, long-term financial conflicts and oil price shocks are the main sources of instability, to which technological shocks can be added, as well (Sameti et al., 2009).

Therefore, based on the above definitions, generally, business cycles include periods of prosperity or expansion and recession or contraction. Within the context of these cycles, recession refers to a period when economic growth is negative and economy goes into a contractual state; in the other words, during these cycles, level of economic activities decreases significantly due to loss of total demand. The intensity of the effects this period is usually to the extent that is evident in various economic sectors such as GDP growth, employment, real income, industrial production, and wholesale and retail prices.

3. LITERATURE REVIEW

In Iran, many studies are carried out regarding the factors affecting business cycles and predicting the occurrence of economic cycles using Granger causality test, simultaneous equations system with vector autoregressive (VAR), wavelet theory, Gaussian mixture models, SCVAR, smooth transition regression, Markov chains (MS-AR), ARIMA linear models, etc., but no research is carried out on prediction using BRT method and this is the first attempt to study prediction with decision tree approach hoping that it would be an starting point in applying this method on future researches that will take place in Iran.

In the past decade, many foreign studies were conducted in the field of decision trees and specifically BRT, among which are the followings:

A research carried out by Berge (2015) using booster to exchange model and another one carried out by Buchen and Wohlrabe (2011) to compare boosting method with other widely studied forecast methods with respect to prediction rate of US industrial production growth rate.

Robinzonov et al. (2012) used boosters to forecast monthly growth of industrial production in Germany and find a good performance with short-term and medium-term horizons. Buchen and Wohlrabe (2011) used boosting method to forecast multiple macroeconomic variables. Bai and Ng (2014) studied boosting method in the context of factor models. Dopke et al. (2015) employed BRT method to measure volatility model of stock market. Ng (2014) conducted a research in line with the current one, in which BRTs are used to forecast recession in US. Key findings suggest that not only the major predictor selected to forecast US recession is very important, but also there are relatively significant predictors that have changed over time. Ng (2014) also ignored marginal effects because regression trees were confined with roots from the effects of possible interaction of the studied predicting variables (i.e. there is no hierarchical structure of the trees).

Also, a research carried out by Dopke et al. (2015) who employed BRT to reevaluate the significance of the major selected indicators to forecast recession in Germany and estimated BRT with data from Germany to study relative importance of predictors and their marginal effects on the probability of recession. Then, using a receiver operating curve, they examined the accuracy of their predictions. The current research findings indicate that interest rate and the period length of major indicators are important. Stock market has also a predictive value since predictive power of short-term interest rates has declined over time so length of the period and stock market have become important. Hence, this study is based upon Dopke et al. (2015) research.

4. RESEARCH METHOD

In this research, seasonal data are taken from 1974 to 2014 and Iran is selected as the statistical society. Also, information on the variables are extracted from Central Bank, Statistical Center of Iran, and World

Bank and (BRT) method is used to forecast recession in Iran. Since to forecast economic events various models can be used, the methods should be selected based on the response variable (quantitative or classified). So, when quantitative response variable is employed in research, usually regression methods or general regression models can be used which require default linear relationship between predicting variables and response variable. On the other hand, if response variables are classified, logistic regression method or linear logarithm can be used which require default linear relationship between independent variables and a logit response variable.

Decision trees can be divided to several parts; one of them is Classification and Regression Tree which was developed by Breiman et al. (1984) for the first time. This method can forecast quantitative (regression trees) or classified (classification tree) response variables. It predicts the event under study through a set of logical terms (rather than linear).

In this study, BRT algorithm is used to classify and forecast economic recession. Here, based upon results obtained by Breiman et al. (1984), recession is regarded as a binary variable.

$y_{t+k} \in \{0,1\} \rightarrow y = 1$ Recession

Aim of the project: Modeling the relationship between the recession and major indicators.

$x_t=(x_{t,1}x_{t,2},\ldots)\rightarrow F(x_t)$

$L(f)=E(\exp(-\tilde{y}_{t+k}F(x_t)))$ (E conditional expectations operator)

Assumed for simplicity $\rightarrow \tilde{y}_{t+k} = 2y_{t+k} - 1 \rightarrow \tilde{y}_{t+k} \in \{-1,1\}$

When $f(x_t)$ intensifies recession in the forecast horizon k, the function decreases. When $f(x_t)$ moves in opposite direction to recession in forecast horizon k, the function increases.

In this case, for conditional probability function we have: $p(\tilde{y}_{t+k} = 1 \mid x_t)$

$$E\exp(-\tilde{y}_{t+k}F(x_t)) = p(\tilde{y}_{t+k} = 1 \mid x_t)\exp(-F(x_t)) + p(\tilde{y}_{t+k} - 1 \mid x_t)\exp(-f(x_t))$$

$$\frac{\partial E\exp(-\tilde{y}_{t+k}F(x_t))}{\partial F(x_t)} = -p(\tilde{y}_{t+k} = 1 \mid x_t)\exp(-F(x_t)) + p(\tilde{y}_{t+k} = -1 \mid x_t)\exp(-f(x_t)) = 0$$

$$F(x_t)=\frac{1}{2}\frac{Lnp(\tilde{y}_{t+k}=1|x_t)}{Lnp(\tilde{y}_{t+k}=-1|x_t)}$$

So, the unknown function $f(x_t)$, in which recession is linked to major indicators, can be calculated by modelling the above ratio.

$f(x_t)$ can be divided to simpler function series of $t(x_t)$:

$$F(x_t) = \sum_{M=0}^{M} T_M(x_t)$$

$f(x_t)$ is a complex function that is used to forecast recession. In order to estimate this function, a weaker function $T(x_t)$ can be used.

In addition, with regard to many factors that influence the onset of economic cycles, deviation from production process (GDPGAP) is used as a dependent variable, and, after data mining and modeling, momentum imports (IM-IM*), total real imports (IMr), unexpected momentum inflation (INF-INFe1) ($\alpha = 0.25$), unexpected momentum inflation (INF-INFe2) ($\alpha = 0.5$), revenue from oil exports (TOGRB), and INF are identified as the most influential variables.

5. EMPIRICAL FINDINGS

5.1. Data Presentation

At first, in this research, a data set with 39 independent variables affecting the business cycles and production gap "GDPGAP" are used as indicators of economic cycles' outbreaks. Then, in order to better clarify BRT model using Weka and R software, relative importance of variables are assessed according to rules of data mining and the most effective variable in economic cycles' outbreaks are chosen. Accordingly, based on the results presented in Table 1, the cited variables are of greater relative importance than other variables in the data set and are more effective in economic cycles' outbreaks so they are used as major variables in measuring the forecast model.

5.2. Relative Importance of Indicators

Breiman et al. (1984) defined the relative importance of an indicator in regression tree as the sum over nonterminal nodes of the squared improvement resulting from using a leading indicator to form splits. Based on this definition, the following Table 2 shows that momentum imports and revenue from oil exports are two important and effective indicators. The overall message of the relative importance of the indicators in the picture is that when we analyze a dynamic model by adding 3 lags to each variables of important indicators, it does not change. The root cause of this weakness is BRT method sensitivity to inclusion of irrelevant predictors in the system of important indicators. This is one of the important characteristics of BRT. Previously, the researchers

Table 1: Attributes selection with data mining

Rank	Attributes	Ranked attributes
1	INF-INFe1	0.1672
2	IM-IM*	0.137
3	INF-INFe2	0.1348
4	INF	0.1142
5	I	0.1139
6	TOGRB	0.1044
7	IMr	0.0912
8	Cl	0.0831

INF: Inflation

Table 2: Relative importance of indicators

Indicators	Rel. INF
IM-IM*	29.1447
TOGRB	20.738
INF-INFe1	19.6169
IMr	14.2218
INF-INFe2	11.736
INF	4.54263

INF: Inflation

found that overfitting is a big problem in macro-economic forecast. Even when only a small number of variables are employed, adding just one variable or other lags of a variable can reduce confined predictive power of the model (Estrella and Mishkin, 1998. p. 55). It should be noted that, because variables' lag make BRT analysis more complicated and its inclusion basically requires predictors' system to be modified, lags are not considered in this boosting method (Figure 1).

5.3. Final Indicators' Impact

Figure 2 indicates curves of marginal (final) effects for indicators affecting recession forecast obtained from BRT model using training data. In fact, curves of final effects show the effect of indicators influencing the probability of recession's outbreak. As it can be seen in the figure, with increase in total real imports, recession probability rate is constant at first and increase in the amount of total real imports has no effect on the probability of recession's outbreak since it is caused by imports of capital goods so increase in this type of imports does not give rise to recession. But, from this level onwards, recessions' probability rate greatly increases with increasing volume of total imports and remains fix at its highest level. According to the curve, momentum imports indicator movement from negative range, which means actual imports are low, has no initial effect on recession's probability rate; however, after crossing the zero

Figure 1: Relative importance of indicator

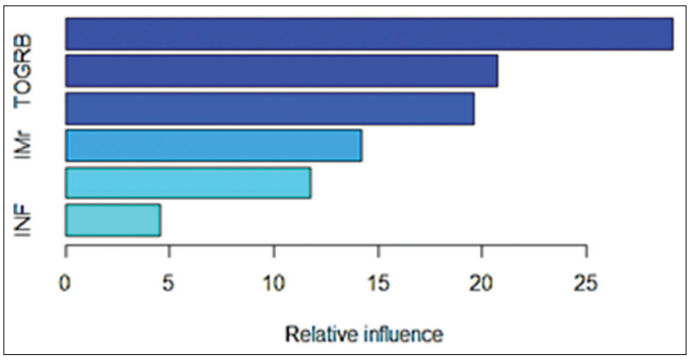

Table 3: Evaluation on training set

Item	Percent
Correctly classified instances	94.51
Incorrectly classified instances	5.49
Kappa statistic	0.8898
Mean absolute error	0.1907
Root mean squared error	0.253
Relative absolute error	38.22
Root relative squared error	50.66
Coverage of cases (0.95 level)	100
Mean rel. region size (0.95 level)	92.99
Total number of instances	164

Figure 2: Marginal effects of indicators

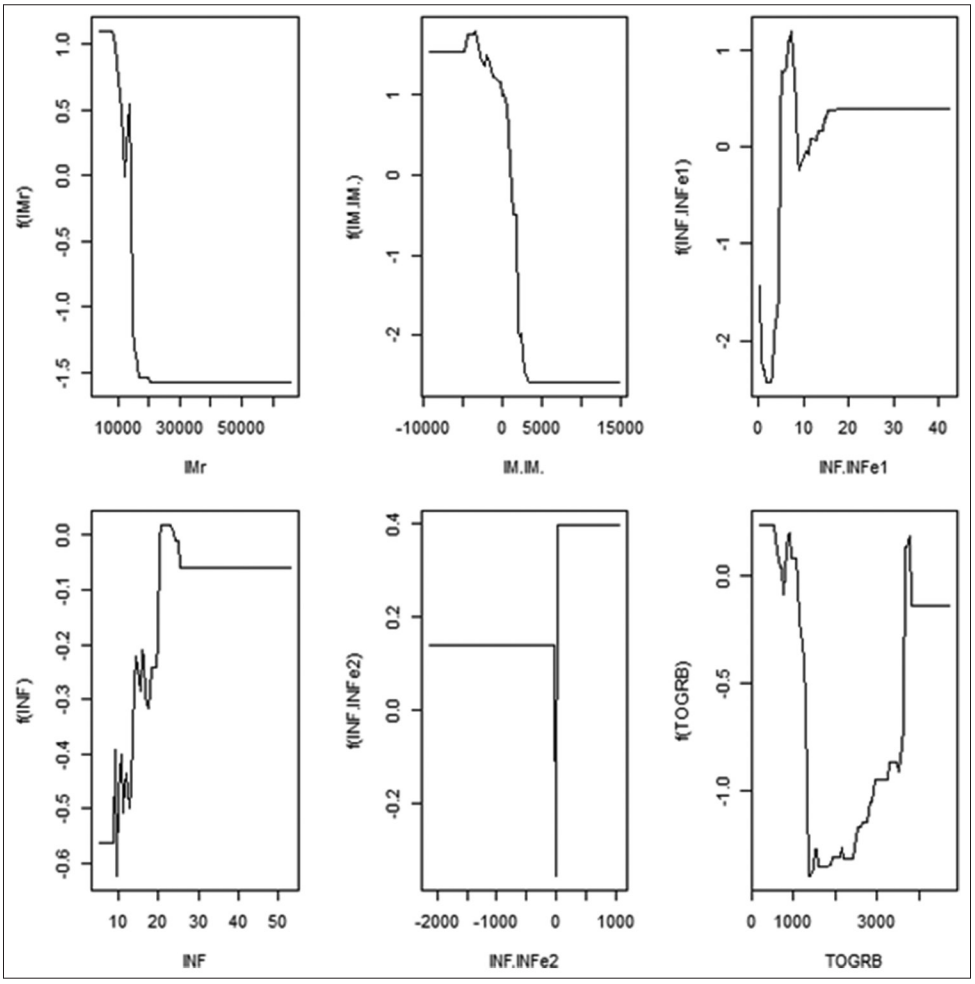

Table 4: Detailed accuracy by class

TP rate	FP rate	Precision	Recall	F-measure	MCC	ROC area	PRC area	Class
0.965	0.077	0.933	0.965	0.949	0.89	0.976	0.969	Yes
0.923	0.035	0.96	0.923	0.941	0.89	0.976	0.965	No

ROC: Receiver operating characteristic, MCC: Matthews correlation coefficient, TP: True-positive, FP: False-positive

point and moving through positive range, the indicator increases recession's probability rate greatly and finally fix it at the highest level. Increase in unexpected momentum INF ($\alpha = 0.25$) leads to continuous decrease in recession's probability rate, as well. As regard to INF indicator, when INF increases in an economy, two different modes may occur. In the first case it is possible that INF be due to supply pressure on the market and brings about increase in recession's probability rate. But, it is also possible that INF be due to demand pressure which result in increased economic activity accompanied by higher prices because of increased demands and brings about decrease in recession's probability rate which is clearly outlined on the chart. Increase in unexpected momentum INF ($\alpha = 0.5$) has no initial effect on recession's probability rate. When it reaches zero, recession's probability rate increases greatly followed by a short decrease and finally remains fix at about 0.05. Also, revenue from oil exports indicator brings about continuous increase in recession's probability rate at the early stages and then recession's probability gradually would reduce and finally it will be fixed at a certain level.

5.4. Model Analysis

According to calculations, in order to estimate the BRT model, maximum depth of the tree is assumed to be 5 which is sufficient to calculate the interaction of variables. Also, the minimum number of observations in each final node is 3. Since better performance of BRT algorithm depends on setting of boosted trees and parameters that stop their branching, reduction level (as a weight index) is an important parameter for each individual tree and every boosted trees. Studies have shown that 0.1 or less reduction rate is usually biased towards an appropriate model so 0.005 and 0.05 are appropriate rates to be considered for datasets smaller than 500 and datasets as big as 50000 (Berge and Jord`a, 2011). As regards, 0.05 is a proper rate for this study. According to the researchers' calculations, BRT model should be trained and estimated with 70% of data (sampling without replacement) and the remaining 30% of data are used to test the model (out-of-sample). Accordingly, to make statistical inference, this process is simulated 1000 times where 5-fold cross validation is used to determine the optimum number of poor learners for each simulation. In this equation, the maximum number of poor learners is fixed at M = 1000. Yet, variance influenced cross validation minimizes the number of poor learners which is usually too small. In all of the 1000 simulations, the optimal average of poor learners is about 123.

Results of BRT model estimation using Weka software is reported as follows in Tables 3-5.

Presented results show that, according to the forecast made in a full sample of data, from a total of 164 classifications, 155 of them have been correctly classified based on the logit boosted model

Table 5: Confusion matrix

Item	A=Yes	B=No
A=Yes	83	3
B=No	6	72

and only 9 cases of misclassification are observed. On this basis, according to Table 5, of the total events in A, (83) forecasts are correct and (3) forecasts are incorrect and of the total events in B, (72) forecasts are correct and (6) forecasts are incorrect. So, in order to evaluate the predictive power obtained in the models of success and failure, there are criteria such as ROC Area and Recall for which the forecast based on statistics calculated in Table 4 shows the highest level and this proves high precision of forecast made by BRT.

6. CONCLUSION

Although experimental results show that machine learning techniques can provide important insights on how to make an economy work, but from the perspective of business cycle forecast applications, these techniques cannot replace empirical forecasts of business cycle, in general, and interpret the estimated probability of recession, in particular. BRT method used in this study is a machine learning technique with remarkable features. One of these features is that BRT method provides a good modeling framework for analysis of relative importance of major indicators. Hence, results show that, momentum imports, revenue from oil exports, unexpected momentum INF, real total import, and INF are more effective in Iran's recession forecast. The results also indicate that BRT method can be a useful technique for analysis of economic policies. Thus, this approach can also be used in forecasting other macro-economic variables.

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