Forecasting economic crises

Mamadou NIANG

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Abstract

The aim of this paper is to identify the potential indicators that may forecast economic recessions in the United States. After an estimation of the recession periods based on the industrial production index by the algorithm of Bry and Boshan covering the period 1980 to 2021, three methods will be used to determine the best model to forecast economic recessions: the traditional approach using probit and logit models and then news approaches using different types of machine learning algorithms: the decision tree and the random forest. The database has been made by extracting variables from the Federal Reserve Economic Data (FRED). After a comparison between our three methods, our results highlight that logistic regression do better than decision trees and random forest in ouf-of-sample with the AUC criterion. However, with different metrics used, the other models do better when it comes to forecast economic crises.

1 Introduction

To begin with, economic crises have always occurred, plunging the economy into recessions. It has been a long time now that many renowned economists tried to find a solution to prevent such events. Indeed, the literature on economic cycles has grown over the centuries. For neoclassicists, crises came along with exogenous shocks. On the other hand, Keynesian school argued that all crises look like previous ones, it is possible to detect a pattern on how crises are formed, in other words, that is how the theory of economic cycles has been forged. If in fact this theory might be verified, it would be possible to prevent economic crises. More recently, with the last recessions which occurred, the ability to forecast economic crises has become an essential need. That is why several actors and institutions of the economic sphere put their interest in such a topic. Indeed, according to Kenny G. and Morgan J. (2011) [9], it were essentially financial factors which were responsible for amplifying crises. The 2007 crisis was due to a significant deterioration of conditions in the U.S housing market as reflected in a sharp increase of the risk of loan default. As a result, we were witnessed of a significant

rise in bank lending interest rates. As well as the housing market's role in the last crisis, a second financial factor was even more responsible : the asset markets. Crises came along with declines in stock prices : everyone panics and starts to sell assets. Such herding behaviour as Keynes would say it, exemplify the devaluation of asset markets thereby worsening firms and households balance sheets. As a result, crises tend to deteriorate the climate of trust between lenders and creditors. While financial factors were the main mechanisms responsible off crises, there are also non-financial elements involved. Indeed, according to Akerlof, G. and Shiller, R. [1], most crises are associated with an increase in the perception of risk. Therefore, several entities such as the OECD lost their credibility regarding households, as it was illustrated by a sharp increase in private saving rate. Besides, following recessions, we often observed a contraction of trades exchanges thereby aggravating the transmission of the shock and its impacts. All of these indicators contributed to plunge the economy even more deeper into a recession.
Therefore, the numerous episodes of economic crises have confirmed the important role of forecasting and the difficulties that can result from it. Predicting the timing, depth and ramifications of a global economic crisis, is extremely difficult. Specific challenges included identifying imbalances or unsustainability of the financial shocks are therefore necessary. However, the last few years, has increased the difficulty of overcoming such challenges due to the development of the transnational interconnections, or the increased variability of economic growth compared to the pre-crisis period, or even the lack of timely data on many crucial economics factors.
In response to crises, the OECD and others international organisations have reviewed and changed their forecast procedures and practices. They centralized early stages of the forecasting cycle. Thereby, this ensures the projections for individual economies since they could learn from others global economies and avoid cross-country spillover effects. Another solutions that has been found was monitoring and develop statistical models when it comes to short term growth. As a result, thanks to the OECD's indicator models for near-term GDP and global trade growth, it improved guidance for projections. Improved and maintain good relationships with businesses are also important since they can provide information and evidence. Moreover, there is also a stronger focus on financial market developments, with financial market indicators which are now integrated into projection processes and macroeconomic models. There has been also an increase on using quantitative analyses in order to improve projections.

Looking up the previous works that has been realized on the ability of forecasting the economy crises, there are in fact several methods to adjust the performance of a forecasting model in times of crises.
Kotchoni, R. and Stevanovic, D. (2016) [10] add the probability of recession to an auto regressive component to improve the predictive power of the model. He used a probit regression which include financial variables like credit spreads. Indeed, adding a non-linear variable in the model, reduce the forecast error to one year ahead in times of recession for the Americans economy.
Whereas, in Canada, according to Clinton, K. (1995) [4] and Bernard, H. (1998) [2], the spread between interest rates on Canadian government bonds ten years and older compare

to the 90-day commercial paper rates, is a good predictor of the cycle. On the other hand, using this kind of cycle modeling requires looking at past periods for recessions. However, in Canada, no official body establishes the dates of recessions unlike the United States where a committee of the National Bureau of Economic Research is responsible for such task. One way to fix this issue, according to Goodwin, T. H. (1993) [7], is to use a regime-shifting Markov model or to use the recessionary periods established by the C.D. Howe Institute on the report of Cross, P. and Bergevin P. (2012) [5].
For the same purpose, Guerron-Quintana, P. and Zhong M. (2017) [8] use a non-parametric model to model the cycle. This is a method borrowed from machine learning, called the k nearest neighbors' method. The first step is to establish the time sequence that minimizes the distance of recent data. Then, the model's forecast error on this sequence is added to the h-period forecast model. Again, they conclude that this approach improves the performance of their forecasting model when the horizon is between one and twelve months. Taieb, S. B. and Hyndman, R. J. (2012) [12] also use the k nearest neighbor method to forecast time series. They correct the iterative forecasting by adding a forecast error. As a result, modeling with the nearest neighbors seems to reduce variance and bias when it comes to forecast crisis.

Overall, that is why one may wonder, are we capable of forecasting economic crises according to the analysis of specific indicators ? To evaluate this ability, we will use different types of tests such as the logistic regression. Results will be compared to predicting models by using machine learning algorithms.

The remainder of the paper is organised as follows. In section 2, we provide an overview of our method by explaining how logistic regression work. We will also develop an overall explanation about different types of machine learning algorithms which permit prediction. The section 3, is used to describe the database and the reason behind the choice of each variable. Section 4 will be dedicated to summarize the results of our tests by applying two methods of calculation, in and out-of-sample estimations. The traditional econometric approach using logistic regression will be compared to machine learning algorithms.

2 Methodology

2.1 The conventional econometric method : logit and probit regression

Our aim is to identify which variables have a significant impact when it comes to forecast economic crises. Let be denoted Y_t, the variable which indicates if there was a recession or not at a given date, depending on macroeconomic indicators denoted by X, our potential indicator variables. Since we are interested on the value that might take Y , only two outcomes are possible. Thus, we are going to use probit and logit regressions in order to find out.

2.1.1 Logit and probit regression

Those two tests are appropriate when it comes to model dichotomous dependent variables i.e., binary variables. In our case, we model Y_t, our target, whether or not there was a recession, depending on others macroeconomic indicators, denoted by X, and a residual error term ε. Since we are looking to estimate Y_t depending on X, it is the equivalent of focusing on the probability of :

$$Y_t = 1 \qquad \text{there is a recession at t}$$

$$Y_t = 0 \qquad \text{otherwise}$$

Thus, the equation's formula for the Probit is :

$$P(Y_{t+k} = 1) = F(\alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + ...)$$

Meanwhile, the equation's formula for the Logit is :

$$P(Y_{t+k} = 1) = F_L(\alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + ...)$$

Where α is denoted as the estimated coefficients and F is the cumulative standard normal distribution function for the probit, denoted respectively F_L for the logit, considered as the cumulative logistic distribution function. In fact, the logistic distribution is quite similar to the normal distribution but the main difference lies in the logit distribution characterized by thicker distribution tails. Later on, we will use only logistic regression.

Since our database contains 120 variables with its lags we will use the HPlogistic procedure to select the most interesting variables. In order to do that, stepwise regression is necessary.

2.1.2 Selecting variables : stepwise regression

Since we already implemented logit regression, to extract the best variables among our database, we will use stepwise regression through the HPlogistic procedure.

The stepwise regression allows us to do a step-by-step iterative model since we are interested by X, the matrix of our independent variables with its lags, $X = (X_1, X_2, \dots, X_n)$, and Y_t, the dependant variable, ie. the target, whether or not there is a recession at a given date :

$$Y_{t+k} = \alpha_0 + \alpha_1 X_{1t} + \alpha_2 X_{2t} + .. + \alpha_n X_{tn}$$

Since stepwise regression combines forward and backward selection. At each step in which a variable will be added, the procedure will checked all the others variables in order to know if they are still statistically significant. Thereby, the procedure will remove the least significant variables, and keep the most significant predictors. As a result, we know now what model we are going to use, ie. the variables with its lags we are going to select in order to test it under in and out-of-sample methods.

2.1.3 In and out-of-sample methods

Since our aim is to identify variables which have an impact on the ability of forecasting economic crises, to enrich our analysis, we will evaluate our model under two methods of calculation : the in and out-of-sample.

Within the in-sample method, the database is constructed with all the entire sample period. Since Y_t is denoted as our target variable and X_{t-h}, our predictive variables, where h is the number of lags, we must estimate the equation below :

$$Y_t = \alpha_0 + \sum_{t=1}^{T} \alpha_t X_{t-h}$$

Our goal is to build a model $\hat{f}(X_{t-h})$ predicting Y_t for a given X_{t-h}.

The in-sample method consist of running our test on the whole sample without splitting it. Then we compare our results to the actual realizations, it's a way to see if our models are effective in reproducing data. When it comes to forecasting, the in-sample method is similar to a training set. In order words, that is why there is a high chance of overfitting, meaning that this procedure may overestimate the model's forecasting ability.

Meanwhile, in the out-of-sample analysis, the model is tested on two data set : we split our database into two samples. Model is run on the first data sample, once it well fitted , we implement our algorithms on the other sample considered as a test set. In other words, we test a forecast value of Y_{t+1}. Thus, we can deduce an error term of forecast $e_{T+1} = Y_{T+1} - \hat{f}(X_{T+1-h})$. We repeat the exercise for others values such as Y_{T+2}, ... , Y_{T+N} and then, we will obtain a predictive error term where $\epsilon = \sum_{t=T_0+1}^{T} e_t$. As you understood, the out-of-sample method is more efficient since it minimizes the risk of over-fitting compared to the in-sample method. Thereby, it gives a more realistic ability of the model to predict.

We will extract from in and out-of-sample, the confusion matrix which gave the predictions depending on the actual observations. Thanks to it, we can deduce the true positive rate, that is to say, the number of recessions we did found in our result, ie when $Y_t = 1$, compared to empirically where a recession in fact occurred too.

2.1.4 The ROC curve, the AUC criterion and the misclassification rate

Overall, in order to know what model, ie. variables with its lags fitted the most for the prediction, we are going to use the ROC curve and the AUC criterion.

The ROC curve (receiver operating characteristic) is a graphical representation evaluating the performance of a classification model for different values of thresholds. This curve model the true positive rate, ie. when there was indeed a recession against the false positive rate, that is to say when our results suggest that a recession occurred but in reality, it didn't happen. In fact, the further this curve is from the diagonal, better the classification rule is. Meanwhile, if the curve is too close or coincides with the diagonal, it means that the classification rule is not better than a random classification. On the contrary, if the curve is below the diagonal, it is a synonym of a weak classification rule.

In order to know if the forecast ability is effective, we will extract the AUC criterion (area under the curve) since it permit to compare our different models. Indeed, the AUC is the best index to say which model did outperform. An AUC criterion close to 1, indicates that the model is doing great. If its value is equal to 0.5, it suggests that the model isn't interesting at all. On the contrary, if the AUC index is equal to 0, it means that the model's predictive capacity is poor.

Finally, we also use the misclassification rate which permits to indicate the performance of a classification model. It equals to :

$$MISC = \frac{\text{false positive + false negative}}{\text{total of the classification}}$$

Since it gives the percentage of miss classified observations, that is to say when our results suggest that a recession occurred but in fact it didn't happen. The closer is it to 0, better the classification rule is. On the contrary, the closer is it to 1 and the worse it is.

Thanks to all of these different indicators , we will be able to know what models fit the most to the data, ie. what variables with its lags are effective for forecasting economic crises. Another method is also possible by using machine learning algorithms, that's what we are going to explain.

2.2 A more contemporary approach : machine learning algorithms

Previously, through different methods of calculation and selection we managed to isolate among our database which variables had a significant impact when it comes to forecast economic crises. Now, our goal is to compare our previous results against machine learning algorithms. Thus, thanks to machine learning, we will extract which variables with its lags are the most effective for forecasting economic crises, then we will compare the model obtained with the model under the logistic regression.

2.2.1 Decision trees algorithms

Decision trees are a popular model used in operations research, strategic planning, and machine learning. They describe how to divide a population of individuals into homogeneous groups according to a set of discriminating variables and depending on a goal. In our case, we are interested by the value that Y might take , whether or not there is a recession depending on the ability of our different indicators, X to forecast.

The recursive partition method is formalized under the acronym CART (Classification and Regression Tree). We deal with "Classification" rule if the variable we are looking to explain or predict is discrete. Meanwhile we used "Regression" if the variable is continuous. This algorithm present many advantages, including an explanatory power which is quite easy to understand since it presents the forecasts obtained in a graphical form. In order to build the tree, first we determine a sequence of nodes. The more nodes there are, the better will be our decision tree's precision.

The considered algorithm requires :

- To define a criterion for an appropriate division among our database in order to select the best variables.

- Then, to know if a node is terminal or no longer divided, is it necessary to choose a decision rule.

- If the node becomes a leaf, each leaf will be assigned to a classes of the variable explained.

- Since we deal with a classification problem, the decision tree will return for new observations, the majority class of the leaf.

We will use the cross-validation method to estimate the reliability of our model. After the selection of the best model we divide our data set into two samples : training and test sets. Then we evaluate the performance of the model in and out-of-sample.

2.2.2 Random forest algorithms

The decision trees algorithm makes good prediction on training sample, but in the test sample, it has the tendency to over-fitting. Since we want to predict observations that we don't have, we will use Breiman random forest algorithm [3] which is more generalizable, even if the interpretation of variable is not possible.

Random forest algorithm makes bagging, that is to say it selects a random sample of variables and observations of our entire base, on which he generates a tree. This procedure is repeated several times. Each time, there is a binary split of the bagged data that aims to compute the association of each input with the target and search for the best split that uses the most highly associated input. When the number of trees increases, the fit statistic has to improve.

The split criteria for each node is Gini. It is also used to measure the variable importance because variables are ranked according to the GiniOOB. Indeed, the out of bag observations (OOB), that is to say the rest of our database after we choose the training sample, provide an error of prediction (errOOB) or misclassification rate after prediction. Therefore, the variable importance X^j is defined by:

$$VI(X^{(j)}) = \frac{1}{M}\sum_{m=1}^{M}(errOOB_m^j - errOOB_m)$$

We denote for the m^{th} tree, the $errOOB_m^j$ as the error of the out of bag sample when the j^{th} variable is permuted. So, the importance variable is obtained by averaging the difference between the out-of-bag error before and after permutation. In SAS, the GINIOOB can be negative, so the splitting rules are spurious. Moreover, we consider that adding a variable is not required when it doesn't permitted to decrease the errorOOB. Therefore, the GINIOOB will be equal to zero.

Furthermore, in SAS, the default value of the fraction inbag is 60% of our sample. There are other parameters fix by default which we don't varying except for the number of trees generated. The option "vars to try" is the root of the number's variables, that is 11. Actually, we used 120 variables in this model because random forest can deal with the missing values of the trade weighted US dollar index and SP500, considering these as new categorical values. "Vars to try" specifies the number of variables to consider to split on in a node. A low number permits to isolate better the importance of variables.

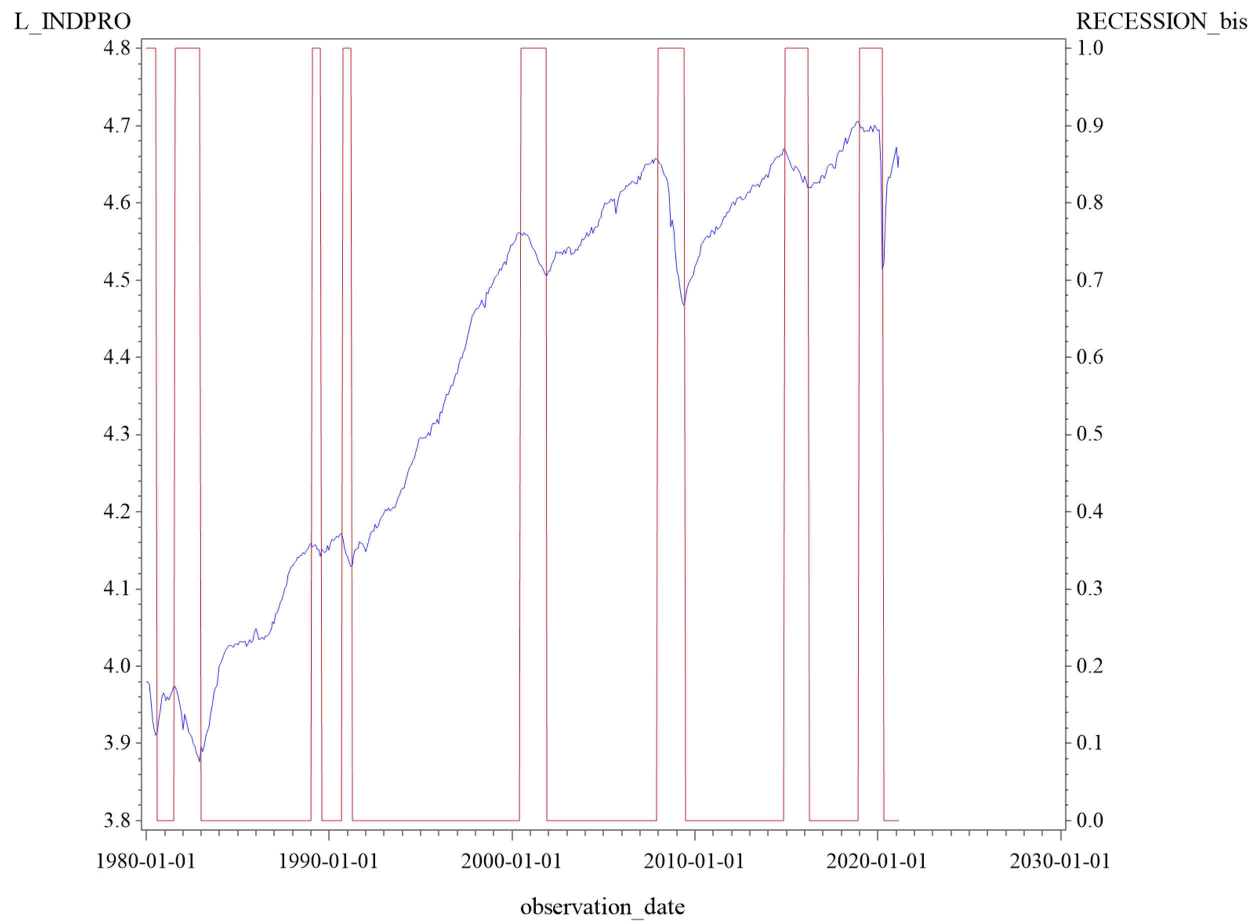
3 The database

3.1 Variables used

In this paper, our aims is to identify variables which are capable of forecasting the economy. We will focus on the U.S financial market since it represents about half of the world's market capitalization. Besides, we know that U.S. recession have a stronger impact on the economy. Indeed, according to Euronext, due to the European crisis in 2011, the CAC 40 stocks have decreased by 30 %. In comparison, due to the U.S recession when the internet bubble burst in 2000, CAC 40 stocks drop of 50% , then 55% during the 2008 crisis.

To begin with, our data base contains variables extracted from the Federal Reserve Economic Data (FRED). The period covered 1980 to 2021 on a monthly basis. We worked with several macroeconomics and financial indicators such as the monetary base M0, M1, M2, month treasury bill (BILL), Wilshire 500 price index (WILL500). Since, we knew the effect of the housing market on recessions, to evaluate its impact, we extracted the number of new private housing units authorized by building permits (HI). Besides, since a highly unemployment rate (UNRATE) is synonym of recessions, we will also use this variable. According to

Figure 1:
Evolution of INDPRO and his recession index



Sahm, C.(2019) [11], the unemployment rate is more efficient than financial market indicators because it produces less false positive recessions. She adds that comparing the three-month average unemployment rate to its lower value over the prior 12 months, predict a recession well before it officially occurred. In the same way, we used the trade weighted U.S dollar index (TWD) to evaluate the impact of trade exchanges. As well, we used the SP500 index (SP500) because it captures market expectations. Nevertheless, since the GDP index on a monthly basis doesn't exist, we implement instead on our database, the U.S industrial production index (INDPRO) seasonally adjusted. Finally, we also used the spread between 10-Year treasury constant maturity minus 3-month treasury constant maturity (SPREAD). Indeed, Estrella, A. and Mishkin, F.S. (1995) [6] already talked about the predictive power of the spread between interest rates even at distant lag, and the bill rate that composes it.

3.2 Bry and Boschan's algorithm : a new indicator based on the U.S industrial production index

We used the NBER based recession indicators in order to identify when recessions occurred. However, since we didn't have enough breaking points, we created a new indicator based on the U.S industrial production index (IPI) thanks to Bry and Boschan's algorithm (1971) which is used by the National Bureau of Economic Research of the United States on monthly data to have our target variable, recession bis. It takes 1 when there is a recession and 0 when there is an expansion. It helps to identify turning points (peaks and troughs) in an economic cycle. The business cycle is defined by a succession of boom and bust phases separated by turning points. Once these are detected, the phases of the cycles are identified by considering an expansion phase, the periods beginning with a trough and ending with a peak while the phases of recession are assimilated through starting with a peak and ending in a hollow. In the figure 1, we saw the match between NBER series and ours, it proves that periods of recession are correctly estimated.

4 Results

4.1 Logit regression (figure (2) et (3))

The HPlogistic procedure that we have set up to select the best model thanks to the stepwise method selection let appear that the best variables to predict recession are : SPREAD lag 2 and 10, BILL lag 2, HI lag , SP500 lag 2, UNRATE lag 1 and 9. Thanks to this model, the AUC score is at 0,99 and the true positive rate is of 0,91 in in-sample method. Whereas, in the out-of-sample, the model gives an AUC score of 0,73 and a true positive rate of 0,43. The misclassification rate is of 18%.

Using the variables selected by the HPlogistic procedure, the model is corrected by applying different steps. First, new variables that are economically important in predicting recessions are taken into account, and then some variables that are correlated with others are removed. The final model of our logistic regression gives an AUC score of 0,98 and a true positive rate of 0,80 in in-sample. Meanwhile, in out-of-sample, the final model gives an AUC score of 0,85 and a true positive rate of 0,75. As a result, we can highlight that the corrected model gives a better outcome, especially in out-of-sample.

4.2 Machine learning algorithms

4.2.1 Decision trees (figure (4))

In order to select the best model for the decision trees, 10-folds cross validation was used with Entropy as the split criterion and Cost-Complexity as the pruning method. The selection of the best model retained the following variables: UNRATE lag 1, 8 and 9, BILL lag 1, SPREAD lag 12. The evaluation of the model lets appear these results : an AUC score of 0,99 and a true positive rate of 1 in in-sample. Whereas, in out-of-sample, the classification tree gives an AUC score of 0,80 and a true positive rate of 0,69. The misclassification rate is of 12%.

4.2.2 Random Forest (figure (5) , (6) et (7))

Firstly, we generate 150 trees inside the random forest. Thus, we obtain a misclassification rate of 20.8% in out-of-sample, and the table of variable importance. It reveals on the top that SPREAD lag 12, 8 and 1 are the most important predictors with UNRATE lag 10 and BILL lag 5. Thus, in order to fit our model, we selected all variables above SPREAD lag 5 (figure 5). Also, we check the average square error and the misclassification error according to the number of tree in figure (6) and (7). We conclude that an increase of the number of tree above 55 trees doesn't permit a significant improvement of the GINIOOB.

Figure 2:

Procédure HPLOGISTIC

Tests d'ajustement de la partition		
Statistique	**Apprentissage**	**Contrôle**
Fraction de vrai négatif	0.9906	0.8267
Fraction de vrai positif	0.9143	0.4375

Test de l'hypothèse nulle globale : BETA=0			
Test	**khi-2**	**DDL**	**Pr > khi-2**
Rapport de vraisemblance	137.2476	7	<.0001

Statistiques d'association				
Rôle	**Indice de concordance**	**D de Somers**	**Gamma**	**Tau-a**
Apprentiss	0.994070	0.988140	0.988140	0.371429
Contrôle	0.734167	0.468333	0.606911	0.137241

Paramètres estimés					
Paramètre	**Estimation**	**Erreur type**	**DDL**	**Valeur du test t**	**Pr > |t|**
Intercept	208.81	71.9205	Infin	2.90	0.0037
SPREAD_lag2	-17.9704	6.1108	Infin	-2.94	0.0033
SPREAD_lag12	8.1397	2.7687	Infin	2.94	0.0033
BILL_lag2	-14.6362	5.0649	Infin	-2.89	0.0039
HI_lag5	0.2476	0.1048	Infin	2.36	0.0181
SP500_lag2	-0.7351	0.2735	Infin	-2.69	0.0072
UNRATE_lag1	10.4939	3.5504	Infin	2.96	0.0031
UNRATE_lag9	-42.7044	14.3576	Infin	-2.97	0.0029

After the variable's selection, the model gives a similar misclassification rate, but the variable importance is quite difference. Indeed, lags 7, 8, 9 and 10 of UNRATE and lags 4, 5, 6 of Bill are ranked before SPREAD lag 12.

Finally, we decide to evaluate the performance of the random forest with the variable's selection of the logistic regression. Moreover, the misclassification rate is the same, but the variable importance reveals that UNRATE lag 4, Bill lag 2 and SPREAD lag 12 are the variables that reduce the GINIOOB the most. Nevertheless, results of random forest can't be interpreted in terms of economics influence.

Figure 3:

Procédure HPLOGISTIC

Tests d'ajustement de la partition		
Statistique	**Apprentissage**	**Contrôle**
r-carré	0.5469	-73.0133
R carré remis à l'échelle max.	0.8115	-120.59
R carré de McFadden	0.7064	-4.6282
Différence des moyennes	0.7262	0.5951
D de Somers	0.9520	0.7075
Fraction de vrai négatif	0.9528	0.8267
Fraction de vrai positif	0.8000	0.7500

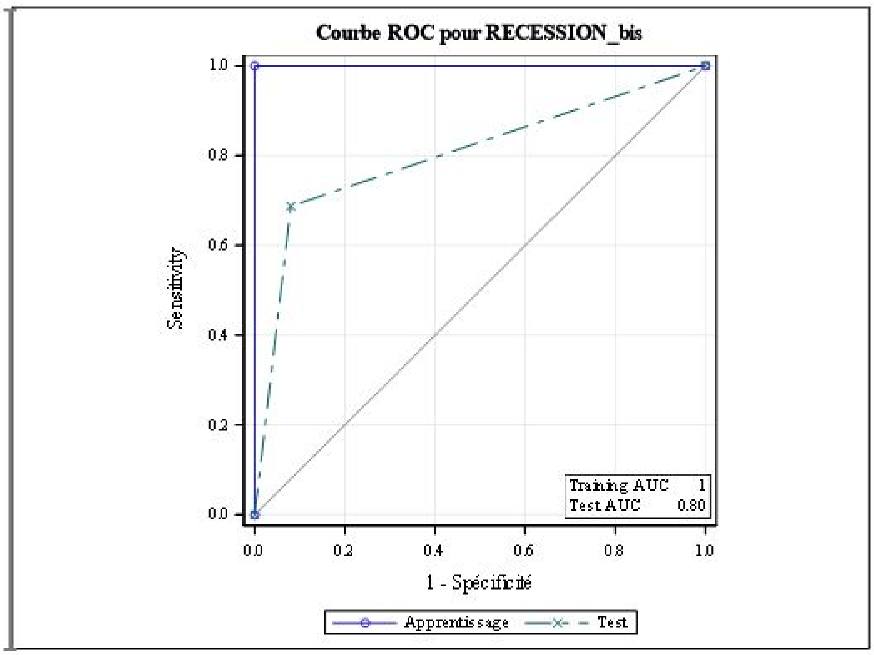
Statistiques d'association				
Rôle	**Indice de concordance**	**D de Somers**	**Gamma**	**Tau-a**
Apprentiss	0.976011	0.952022	0.952022	0.357852
Contrôle	0.853750	0.707500	0.748018	0.207326

Paramètres estimés					
Paramètre	**Estimation**	**Erreur type**	**DDL**	**Valeur du test t**	**Pr > |t|**
Intercept	107.23	28.5860	Infin	3.75	0.0002
M0_lag5	0.09632	0.2572	Infin	0.37	0.7080
M0_lag7	0.6284	0.2133	Infin	2.95	0.0032
SPREAD_lag2	-6.8514	1.9900	Infin	-3.44	0.0006
SPREAD_lag12	3.0895	1.1004	Infin	2.81	0.0050
BILL_lag2	-7.6725	2.1169	Infin	-3.62	0.0003
WILL500_lag4	0.1022	0.09574	Infin	1.07	0.2857
HI_lag5	0.07496	0.03809	Infin	1.97	0.0491
SP500_lag2	-0.4163	0.1203	Infin	-3.46	0.0005
UNRATE_lag4	1.2445	2.5346	Infin	0.49	0.6234
UNRATE_lag8	-17.7344	5.0432	Infin	-3.52	0.0004

Figure 4:

Procédure HPSPLIT

Matrice de confusion basée sur le modèle			
	Prédit		Taux d'erreur
Réel	0	1	
0	106	0	0.0000
1	0	35	0.0000
0	69	6	0.0800
1	5	11	0.3125



Importance des variables			
	Apprentissage		
Variable	Relatif	Importance	Effectif
UNRATE_lag9	1.0000	5.0039	3
SPREAD_lag12	0.7384	3.6948	1
BILL_lag4	0.6102	3.0535	2
UNRATE_lag1	0.4291	2.1470	1

Figure 5:

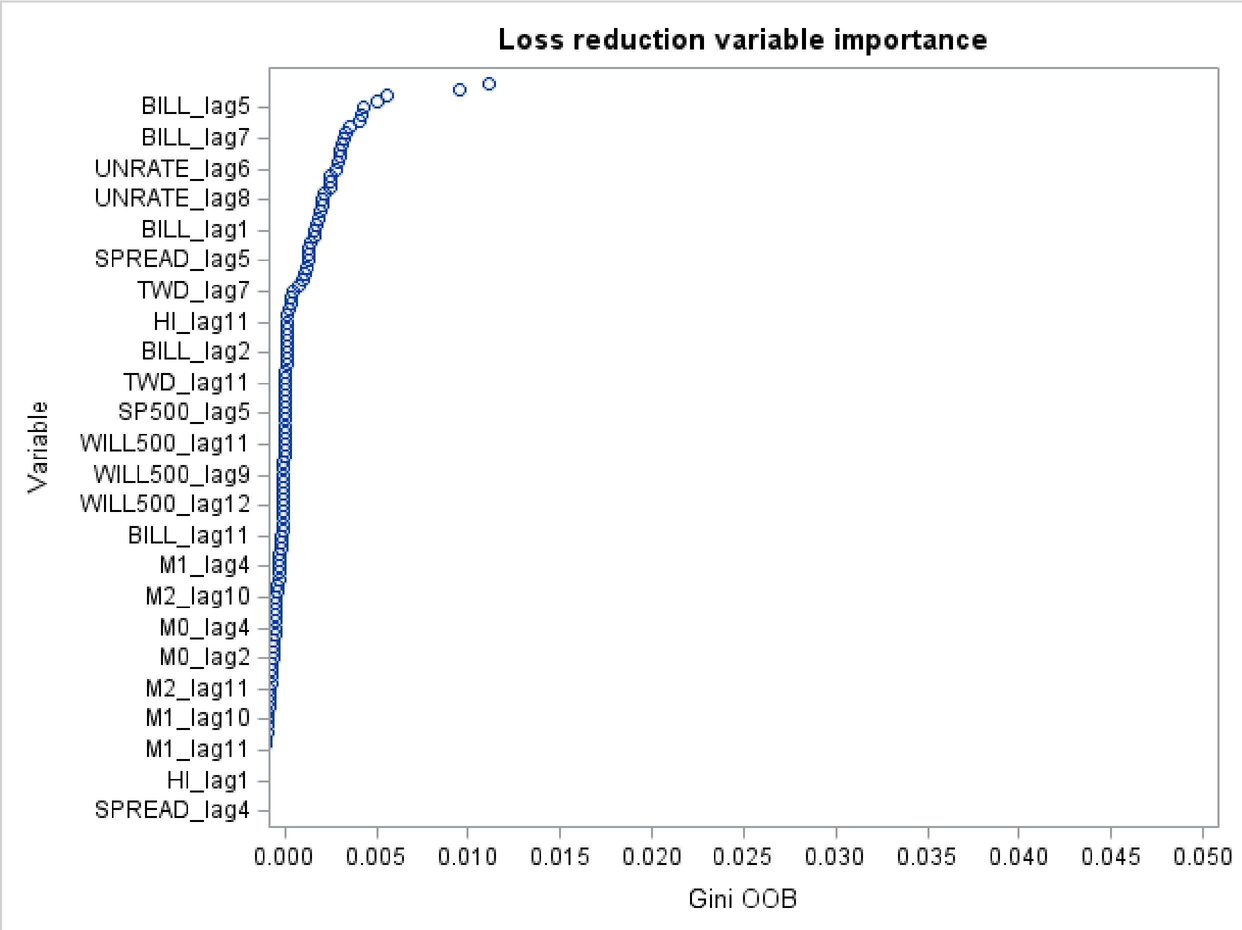


Figure 6:

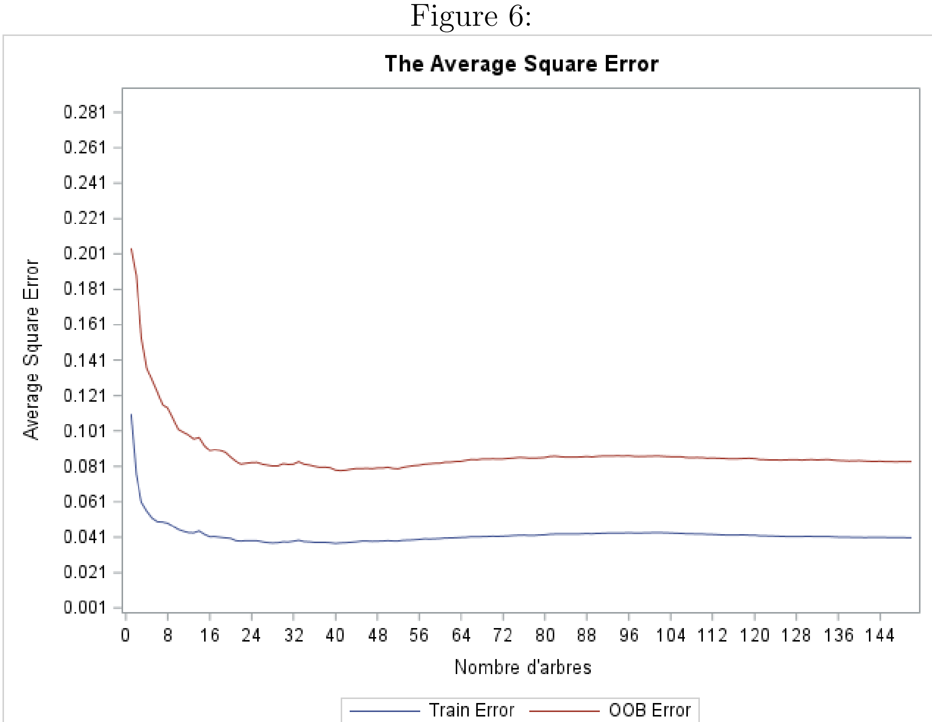
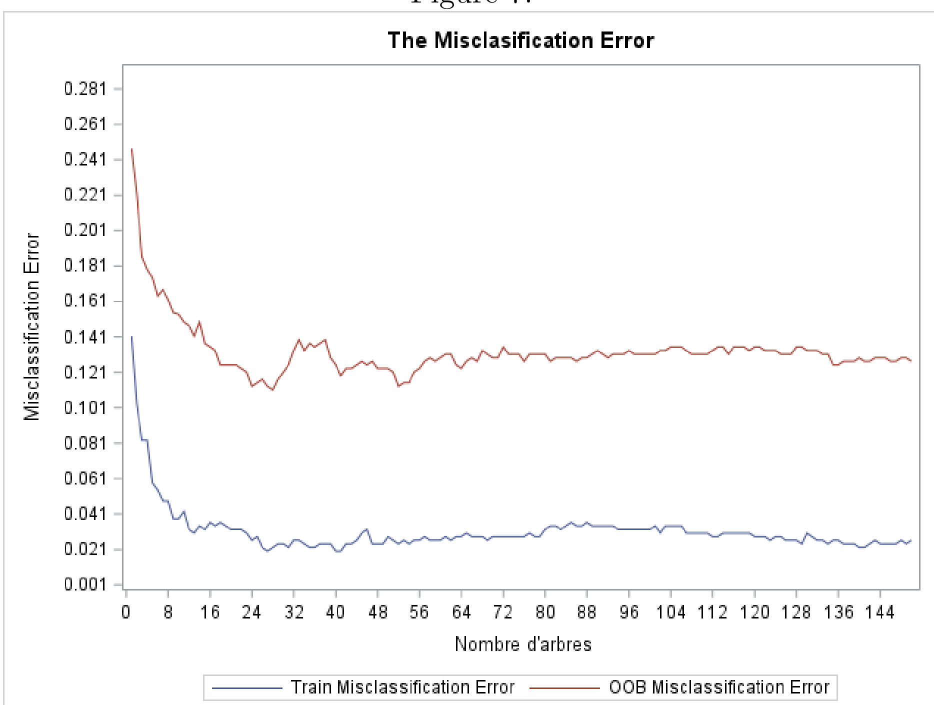


Figure 7:



The Misclasification Error
Misclassification Error
0.281
0.261
0.241
0.221
0.201
0.181
0.161
0.141
0.121
0.101
0.081
0.061
0.041
0.021
0.001
0 8 16 24 32 40 48 56 64 72 80 88 96 104 112 120 128 136 144
Nombre d'arbres
Train Misclassification Error
OOB Misclassification Error

5 Conclusion

To conclude, we know what variables are relevant when it comes to forecast economic crises. Indeed, the spread lag 12 with the unemployment rate suggest that our models are efficient since we obtain high metrics scores. In regards to the methodology, in out-of-sample, the logistic regression is doing better than machine learning algorithms since the AUC score and the true positive rate are better. Meanwhile, as for in-sample methodology, we found that the best model in order to predict crises is the decision tree algorithm. However, when we choose a different metric score, it appears that results are quite different. Indeed, as for the misclassification rate, it was the decision trees which perform the most in out-of-sample. The random forest's result are not as good as our others algorithms. Thus, in order to improve our analysis, it could have been interesting to test others criterion's since we seen that depending on the metric uses, the outcome is quite different.

Most recently, with the COVID-19 pandemic, a lot of countries provided assistance to their companies through different types of solution such as delaying payment, solidarity funds, or even burden transfer. As a result, indebtedness is rising in several countries. The European Central Bank fears a financial crisis. Is it more important than ever to find reliable and trustworthy solutions in order to forecast economic crises, it could be a useful tool of guidance for economies.

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