Machine Learning in Economics
(458657)

replication paper

Early Warning System for Fiscal Stress

comparing the traditional logistic regression approach with random forest

Department of Economics
University of Bern

Spring Semester 2022

submitted by Bela Tim Koch

Contents

1 Introduction and Literature Review

Since the latest Great Recession with its corresponding deterioration of public finances, the monitoring and prevention of fiscal crises has become increasingly prominent in the political debate, leading to an increasing demand for the development of reliable and early indicators that signal possible fiscal stress. In order to be able to assess countries' vulnerability to fiscal distress ex-ante, the literature is increasingly devoted to the development of early warning systems for fiscal stress, which build on early warning systems for banking and currency crises (Honda, Tapsoba, and Issifou 2022). The standard tool used in the literature for early warning systems are the signalling approach as well as discrete dependent variable models, such as logistic regression (Jarmulska 2020). However, as an alternative to the traditional methods, early warning models based on machine learning techniques are proposed, claiming a possible improvement of prediction accuracy (Beutel, List, and Schweinitz 2019).

This paper aims to replicate some of the work done by Jarmulska (2020). Particular emphasis is placed on the comparison of the traditional method, i.e. a logit model with a least absolute shrinkage and selection operator, and a novel approach of using an implementation of a random forest algorithm. Since machine learning algorithms such as the random forest is often accused of a lack of interpretability, ways of interpreting the developed model are presented.

2 Model Describtion

2.1 Performance Metrics

Jarmulska (2020) uses sensitivity, specificity, their average as well as the area under receiver operating curve (AUROC) as measures to assess the effectiveness of the early warning models. Since sensitivity corresponds to the proportion of stress episodes correctly classified whereby specificity corresponds to the proportion of tranquil episodes correctly classified, these metrics are dependent on the threshold, which determines whether a period is classified as stress or tranquil episode (Jarmulska 2020). In this paper, this threshold is specified by maximizing the weighted sum of sensitivity and specificity. In contrast, the AUROC is a robust measure, as all possible thresholds are taken into account in their calculation. This measure represents the area under the receiver operating curve, which displays the trade-off between the true positive rate (i.e. sensitivity) and the false positive rate (i.e. 1 - specificity). Theoretically, the AUROC can be between 0 and 1 (perfect classifier), whereby random guessing would result in to a value of 0.5 (Fawcett 2006).

2.2 Logit Model with LASSO penalisation

Jarmulska (2020) implemented two version of discrete dependent variable models (logit regression), first a standard logit model with ordinary least squares estimates and second a logit model with a least absolute shrinkage and selection operator (LASSO) penalization. These models are often used as the standard econometric approach, which is why they are used as the benchmark in this study.

Ordinary least squares estimates often have low bias but large variance, reducing prediction accuracy - the prediction accuracy can sometimes be improved by shrinking some coefficients towards zero to sacrifice bias in order to reduce variance of the predicted values and possibly improve overall prediction accuracy (Tibshirani 1996). To do so, LASSO penalization as proposed in Tibshirani (1996) can be applied. Because of this characteristics, only the logit LASSO model is considered in this replication.

Following Hastie et al. (2009), the LASSO problem in the Lagrangian form is given as follows:

$$\hat{\beta}^{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \frac{1}{2} \sum_{i=1}^{N} (y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{1}$$

whereby λ corresponds to the penalization parameter. As can be seen in Equation (1), the higher λ, the higher the number of coefficients shrunk to zero. Here, λ is chosen by 5-fold cross-validation, maximizing the AUROC.

2.3 Random Forest

Building upon decision trees, which divide the predictor space into

zuerst ganz kurz definition cart (ev. mit anderer quelle als jarmulska)

dann ganz kurs warum cart zu rf

dann ganz kurz rf

Gini index

$$g(w) = \sum_{k \neq j} p_{wk} p_{wj} = \sum_{k} p_{wk}(1 - p_{wk}) \tag{2}$$

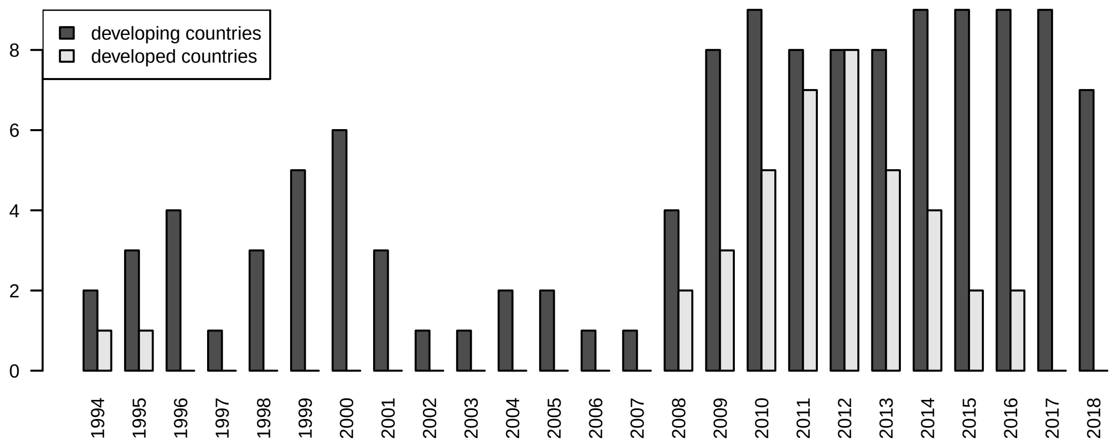
3 Data Describtion

3.1 Dependent Variable

definition of a fiscal stress event follows Dobrescu et al. (2011) siehe die tabelle

empirical/historical data about fiscal stress events

Figure 1: Distribution of Stress Periods



3.2 Explanatory Variables

Table 1: Means of Explanatory Variables

Variable	All periods	Tranquil periods	Stress periods	P-value	Significance
Competitiveness and domestic demand					
Current account balance	-0.52	0.28	-4.57	0.00	yes
CPI	4.26	3.68	7.18	0.00	yes
Credit to GDP change	1.42	1.58	0.58	0.40	no
Unemployment change	-0.04	-0.14	0.48	0.00	yes
Consumption dynamics	-4.21	-3.80	-6.31	0.00	yes
Export share dynamics	0.60	0.78	-0.36	0.08	no
Financial					
Fixed capital formation dynamics	7.82	8.00	6.96	0.34	no
FX rate dynamics	1.87	0.69	7.82	0.00	yes
Fiscal					
GDP dynamics	2.90	3.14	1.71	0.00	yes
China GDP dynamics	9.62	9.63	9.59	0.55	no
US GDP dynamics	2.46	2.58	1.82	0.00	yes
Labor market					
Labor productivity dynamics	1.76	1.90	1.05	0.00	yes
GDP per capita	26.13	28.08	16.28	0.00	yes
Macroeconomic and global economy					
Interest on debt	3.58	3.32	4.92	0.00	yes
US interest rates	4.27	4.40	3.64	0.00	yes
Net lending	-2.47	-2.06	-4.55	0.00	yes
Oil price dynamics	5.05	5.87	0.89	0.03	yes
Currency overvaluation	-33.76	-31.59	-44.73	0.00	yes
Public debt	58.51	56.69	67.71	0.00	yes
VIX	20.17	20.07	20.70	0.74	no

4 Empirical Results

4.1 Performance

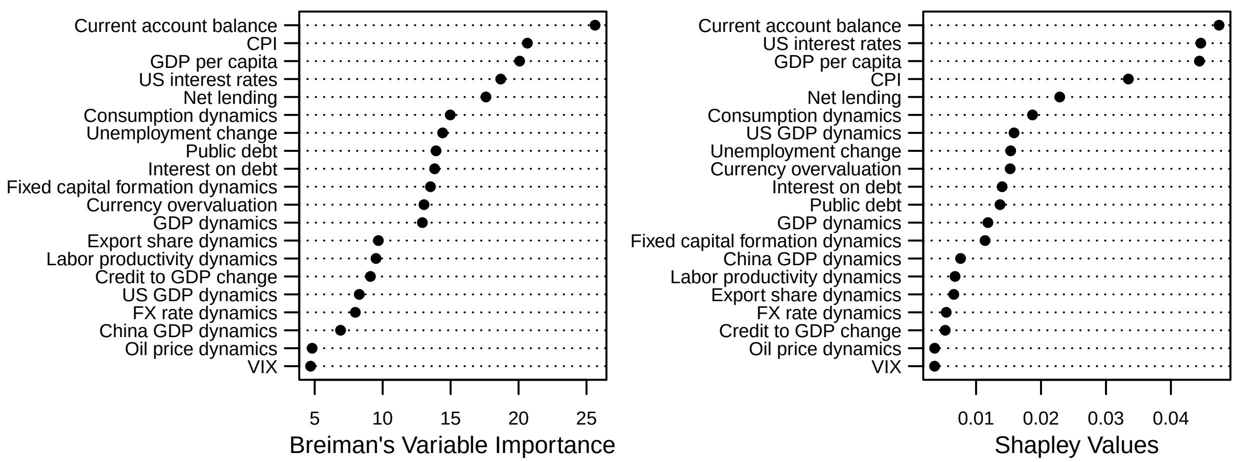
Table 2: Average prediction accuracy of early warning models for years 2009-2018

	Logit LASSO		Random Forest	
	advanced dummy	GDP per capita	advanced dummy	GDP per capita
% of correctly classified stress episodes	85.8	77.23	89.56	88.61
% of correctly classified tranquil episodes	56.4	65.86	65.33	69.63
Average	71.1	71.55	77.44	79.12
AUROC	0.84	0.85	0.88	0.89

4.2 Interpretability of Random Forest Algorithm

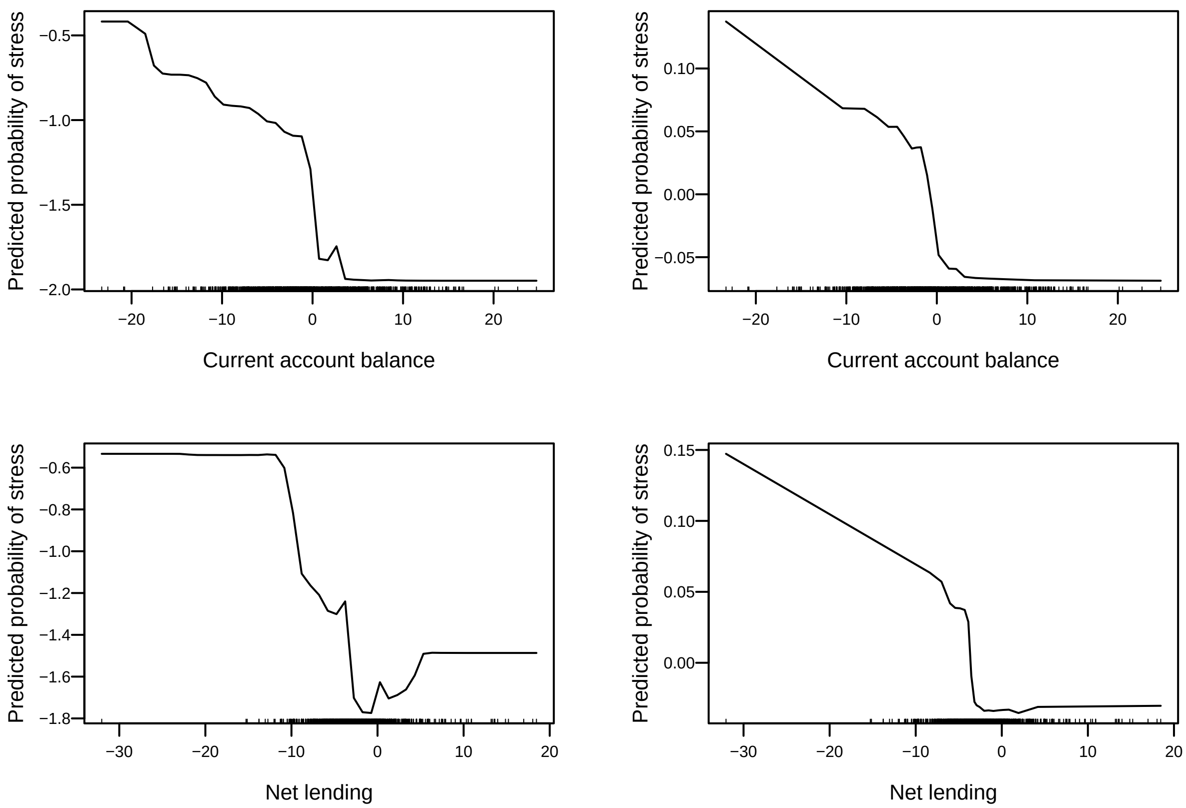
4.2.1 Variable Importance and Shapley Values

Figure 2: Variable Importance and Shapley Values of Predictors used



4.2.2 Partial dependence plots and Accumulated local effects plots

Figure 3: Partial Dependence and Accumulated Local Effects Plots



5 Conclusion

6 References

The code and data used for this project can be found in the corresponding GitHub-repository: `https://github.com/bt-koch/ML-in-Economics`.

Beutel, Johannes, Sophia List, and Gregor von Schweinitz. 2019. "An evaluation of early warning models for systemic banking crises: Does machine learning improve predictions?" IWH Discussion Papers 2/2019. Halle Institute for Economic Research (IWH). https://ideas.repec.org/p/zbw/iwhdps/22019.html.

Dobrescu, Gabriela, Iva Petrova, Nazim Belhocine, and Emanuele Baldacci. 2011. "Assessing Fiscal Stress." *IMF Working Papers* 11: 100.

Fawcett, Tom. 2006. "An Introduction to ROC Analysis." *Pattern Recognition Letters* 27 (8): 861–74. https://doi.org/https://doi.org/10.1016/j.patrec.2005.10.010.

Hastie, Trevor, Robert Tibshirani, Jerome H Friedman, and Jerome H Friedman. 2009. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*. Vol. 2. Springer.

Honda, Jiro, René Tapsoba, and Ismael Issifou. 2022. "When Do We Repair the Roof? Insights from Responses to Fiscal Crisis Early Warning Signals." *International Economics*. https://doi.org/https://doi.org/10.1016/j.inteco.2022.02.008.

Jarmulska, Barbara. 2020. "Random Forest Versus Logit Models: Which Offers Better Early Warning of Fiscal Stress?" *ECB Working Paper Series No 2408 / May 2020*.

Tibshirani, Robert. 1996. "Regression Shrinkage and Selection via the Lasso." *Journal of the Royal Statistical Society: Series B (Methodological)* 58 (1): 267–88.