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Do sanctions trigger financial crises?

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ABSTRACT

We investigate the effect of sanctions on the occurrence of financial crises. We use the Classification and Regression Tree (CART) algorithm to check whether binary classification mechanism selects sanctions as a predictive factor for the different types of financial crises. We find that trade sanctions matter for the increased probability of banking crises, while military sanctions are associated with currency crises. We find no evidence of the effect of sanctions on sovereign debt crises. We furthermore indicate which variables and their respective thresholds serve as potential harbingers of financial crises.

1. Introduction

Sanctions have become a common tool of coercion in international politics (Morgan et al., 2023). They aim to damage the economy of the target country in order to force it to change its policies. The economic effects of sanctions can occur through several channels such as trade restrictions (Afesorgbor, 2019) or a decrease in foreign direct investment (Biglaiser and Lektzian, 2011). However, sanctions can also have detrimental effects on the target economy by triggering financial crises.

Given the devastating effects of financial crises on economic growth (Reinhart and Rogoff, 2009), this channel is fundamental for assessing whether and how sanctions are able to achieve their objectives. It appears as a surprise, therefore, that only a handful of papers have examined how sanctions can induce financial crises. Peksen and Son (2015) have concentrated on currency crises while Hatipoglu and Peksen (2018) have focused on banking crises, both for the years from 1970 to 2005. Both studies find that sanctions induce financial crises, using binary regression models on cross-country datasets.

We provide new evidence on the effect of sanctions in triggering financial crises by delineating three novel contributions. First, we adopt a holistic approach, evaluating the effect of sanctions across the spectrum of financial crises, including banking, currency, and sovereign debt. Sanctions can trigger currency crises by causing capital outflows and reducing access to foreign reserves needed to support the exchange rate. They can cause banking crises by reducing the access to foreign credit, increasing the exchange rate risk, and encouraging bank runs. They can trigger sovereign debt crises through the loss of fiscal revenues and higher borrowing costs for the target country.

Second, we use the Classification and Regression Trees (CART) algorithm, a robust decision tree-based analysis tool, to dissect the intricacies of sanctions-induced crises (Laborda and Laborda, 2017; Galil et al., 2023).This approach was introduced by Breiman et al.

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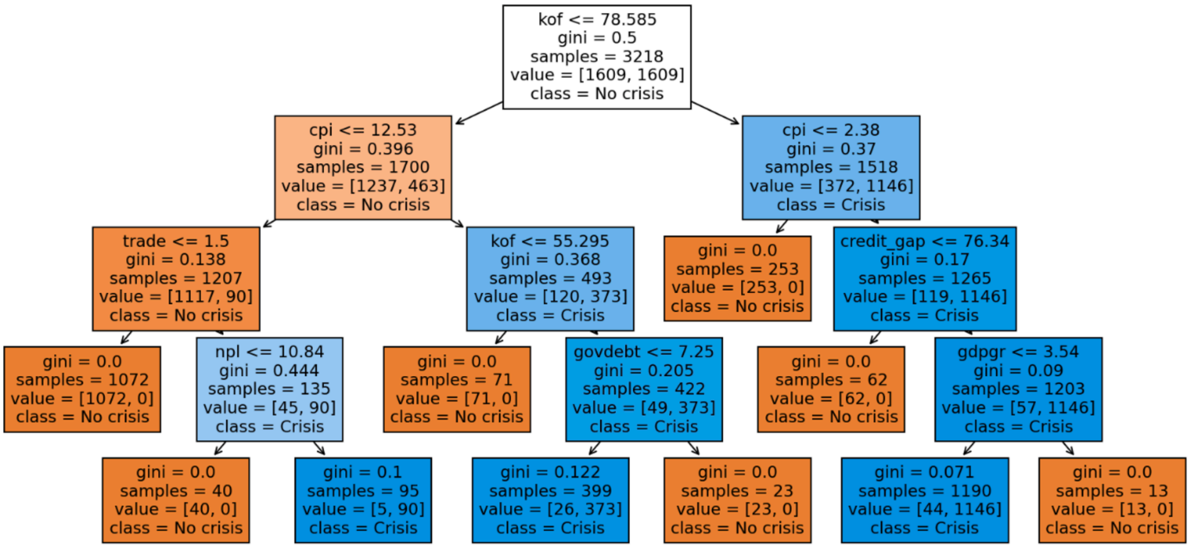


Fig. 1. Binary classification tree for banking crises with regressors having lag 0.

(1984) and has since been applied in various fields (Laborda and Laborda, 2017; Galil et al., 2023). In the context of financial crises, the Binary Classification Tree was first used by Duttagupta and Cashin (2008) to predict banking crises. Manasse and Roubini (2009) as well as Savona and Vezzoli (2015) applied CART to analyze the drivers of sovereign debt crises.

Third, we utilize an updated and extensive dataset from Felbermayr et al. (2020), spanning from 1950 to 2016, encompassing recent geopolitical developments, such as the sanctions imposed on Russia post-2014. This enhancement broadens our analytical scope, enabling a comprehensive investigation of the sanctions' repercussions in contemporary settings.

The outcomes of our study are threefold: we quantify the impact of various sanctions on financial crises incidence; we pinpoint predictive indicators for crisis foresight, offering threshold values for that, once crossed, can indicate potential economic problems; and we map out predominant scenarios that culminate in a financial crisis.

The remainder of the paper proceeds as follows. Section 2 describes data and methodology. Section 3 displays the results. Section 4 provides concluding remarks.

2. Data and methodology

Data on sanctions come from the novel Global Sanctions Database (Felbermayr et al., 2020), which provides a detailed record of all international sanctions from the period 1950–2019. Data on financial crises is retrieved from Laeven and Valencia (2020).

To conduct our research, we use the Classification and Regression Trees (CART) methodology. Similar to logit and probit models, CART is used for classification and regression tasks but it offers several critical advantages that enhance the robustness and depth of our analysis.

First, CART is a nonparametric technique, thereby making no assumptions about the parameters of the data distribution. Second, CART can account for heterogeneity in the data, recognizing that various combinations of variables could precipitate a financial crisis (e.g., current account imbalances with fixed exchange rates, credit booms financed by bank external debt). Thus, it is better suited than conventional binary models to capture non-linear interplays between the variables. Third, CART robustness to common data issues, e.g. outliers, missing values, multicollinearity, heteroskedasticity, and distributional error structures, ensures the integrity of our classification outcomes, providing a clear edge over binary regression models.

CART works as follows. It first identifies the variable that can be used to reasonably partition (make the purest split of the "0″ and "1″ observations with the minimum number of misclassifications) the data into two groups – "crisis" and "no crisis" observations. Once the dataset is split into two subsets at the first (root) node, each half of the tree (left and right sub-nodes) is then separately analyzed. The logic for splitting the sub-nodes is the same: search for the variable that best splits the group into two subsets – "crisis" and "no crisis". The algorithm continues until we obtain the purest classification.

It should be emphasized that CART is not based on a probabilistic model. It means that there is no probability level or confidence interval associated with predictions derived from the tree. Therefore, there is no way to perform statistical tests on the results or calculate marginal effects.

Our target variable is binary, i.e. "crisis" or "no crisis". We do separate trees for banking, currency and sovereign debt crises. The set of potential predictors for different crises events includes the following variables: annual GDP growth (*gdpgr*), CPI (*cpi*), central government debt (% of GDP) (*govdebt*), KOF globalization index (*kof*), Chinn-Ito Index of financial openness (*chinn*), the level of democracy (*polity-V index*), broad money to reserves ratio (*m2*), non-performing loans to assets (*npl*), z-score (*z*), cost-to-income ratio of the banking industry (*cost*), credit-to-gdp gap (*credit_gap*) and the variable, indicating the number of countries which imposed different types of sanctions on the target economy (*financial, trade, arms, military, other*). The choice of potential predictors is partially motivated by previous research (Peksen and Son, 2015; Hatipoglu and Peksen, 2018) and by our heuristic considerations. The data for all the financial and economic indicators come from the World Development Indicators database. The democracy variable is taken from the Polity V dataset, the KOF globalization index comes from KOF Swiss Economic Institute, while the data on the Chinn-Ito index is from the website of Chinn and Ito.

To mitigate endogeneity issues, we construct trees for regressors with lags 0, 1, 2 and 3. Thus, we end up with 12 trees, four for each type of financial crises. Our sample consists of 2323 observations, with 24 banking crises episodes, 28 currency crises and 6 sovereign debt crises, which means an unconditional crisis probability is 1 % for banking crises, 1.2 % - for currency crises and 0.3 % - for sovereign debt crises. To account for the obvious imbalance of classes when building a tree, we use a hyperparameter *"class_weight = balanced"*. We use a standard binary classification tree method from python library *scikit-learn*. Other hyperparameters for the trees are selected with the help of *RandomSearchCV* algorithm and are available upon request. Descriptive statistics of all variables are displayed in Table 1 in the Appendix.

3. Results

The result for each of the models is presented as a tree. We present the trees for banking crises, currency crises, and sovereign debt crises, respectively, with regressors having lags 0–3 in Panels A1 to A3 in the Appendix.

We take the tree for banking crises with regressors having lag 0 (Fig. 1) to illustrate the results we obtain from each of the trees. The root node of the tree is represented by the KOF globalization index. This is the most powerful variable to split our data into crisis/no crisis observations. The threshold for the KOF index indicated in the node is equal to 78.585. Thus, a random observation with the KOF index lower than this threshold will go to the left node and have a "no crisis" prediction. If the KOF index is higher than 78.585, the observation will go to the right node and have a "crisis" prediction. At this first stage the split of observations to "crisis" or "no crisis" groups is not perfect since there can be misclassification errors. The algorithm then continues splitting, searching for the next variable which allows to improve the classification. The algorithm takes the CPI and continues the splitting with the same logic.

The final tree shows us a chain of simple rules that end up in a prediction. Conditional on this chain, the final prediction can be different, and this allows for the fact that not all crises are alike.

In our case for the banking crises tree, we observe three blue chains, which end up in the "crisis" prediction. They are as follows:

– a combination of a moderate KOF index (<78.6), moderate CPI (<12.53), trade sanctions imposed by more than one country (>1.5) as well as high level of NPL (>10.84) can lead to a banking crisis;
– a combination of the KOF index in the range 55.3<KOF<78.6, high CPI (>12.53), moderate government debt (<7.25) can end up in a banking crisis.
– a combination of a high KOF index (>78.6), moderate and high CPI (>2.38), higher levels of credit gap (>76.34), and high annual GDP growth (>3.54) can lead to a banking crisis.

Thus, for this tree we find that trade sanctions along with other factors can lead to an increased probability of a banking crisis. Among all the trees for banking crises with a different lag length, this tree is the only one where sanctions appear as a splitting variable.

As a by-product of our baseline analysis, we are able to make up a list of important variables predicting the occurrence of a banking crisis. Across all the trees for banking crises, these predictors include the KOF globalization index, which appears to be the most powerful splitter for crisis and no-crisis episodes in all the cases; macroeconomic fundamentals, such as the CPI level, government debt and annual GDP growth rate; the variables that reflect the performance of the banking sector (the ratio of non-performing loans to assets) as well as the evolution of credit dynamics (credit gap) and institutional variables (Polity V index). Our list of important predictors confirms the findings of Hatipoglu and Peksen (2018), who document that stagnant growth and negative economic outlook as well as the indicators of excessive lending increase the probability of systemic banking crises.

As for currency crises, results from the four trees suggest that the number of countries which imposed military sanctions increases the odds of a currency crisis in a target economy. The threshold for the variable is 0.5. This means that even if these are unilateral sanctions imposed by a single country, they are associated with an increased probability of a currency crises in case the sanctions are exacerbated by the high levels of credit gap and the KOF globalization index (tree for regressors with lag 2) or by a high credit gap and a low z-score (tree for regressors with lag 3). We partially confirm the results presented in Peksen and Son (2015). They demonstrate that sanctions can be detrimental to financial stability, but in contrast to their research we find that the main danger comes from military sanctions and not financial or trade restrictions.

Apart from it, the list of the most powerful predictors for currency crises includes the CPI index, the money multiplier, the Polity V index, z-score, credit gap and the KOF globalization index. Our findings corroborate evidence on the importance of macroeconomic fundamentals (CPI index, and broad money to reserves ratio) for predicting currency crises, provided by early warning systems of the second generation (Kaminsky and Reinhart, 1999; Crespo Cuaresma, 2008; Aydin, 2023).

The list of indicators, which are associated with the increased probability of sovereign debt crises, consists of the z-score index, annual GDP growth rate and the KOF globalization index. Sanctions do not appear among the splitting variables in any of the trees. Thus we conclude they do not affect the crisis probability. Most common scenarios leading to sovereign debt crises are the combination of low GDP growth and low z-score (for the tree with the first lag of regressors) as well as a low z-score and a low KOF index (for models with lag 2 and lag 3). The appearance of the z-score among the list of important predictors highlights a strong connection between sovereign debt sustainability and the performance of the national banking sector (Dell'Ariccia et al., 2018; Fiordelisi et al., 2020).

4. Conclusion

Utilizing the CART algorithm, we investigate whether sanctions serve as a reliable harbinger for various types of financial instability, including banking, currency, and sovereign debt crises.

Our empirical analysis reveals a nuanced landscape. We find that trade sanctions play a role in increasing the probability of banking crises, while military sanctions are associated with currency crises. At the same time, we find no evidence that sanctions affect sovereign debt crises. In addition, we derive a set of variables and their critical thresholds, that are relevant to monitor in order not to miss the seeds of future financial crises.

Our results have economic and policy implications. They demonstrate how geopolitical actions like sanctions cause financial crises, highlighting the interconnectedness of the political and economic spheres. They show that the impact of sanctions on financial crises depends on several economic factors and is therefore complex to predict. They also suggest that policymakers can never link sovereign debt crises to the implementation of sanctions.

Further research can be done to investigate relevant factors for predicting complex financial crises, including twin and triple crises. Taking into account the severity of sanctions and the type of actors involved could also provide additional evidence on how sanctions might affect the likelihood of crises.

CRediT authorship contribution statement

Maria Shchepeleva: Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mikhail Stolbov:** Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Laurent Weill:** Writing – review & editing, Writing – original draft, Supervision.

Declaration of competing interest

None.

Data Availability

Data will be made available on request.

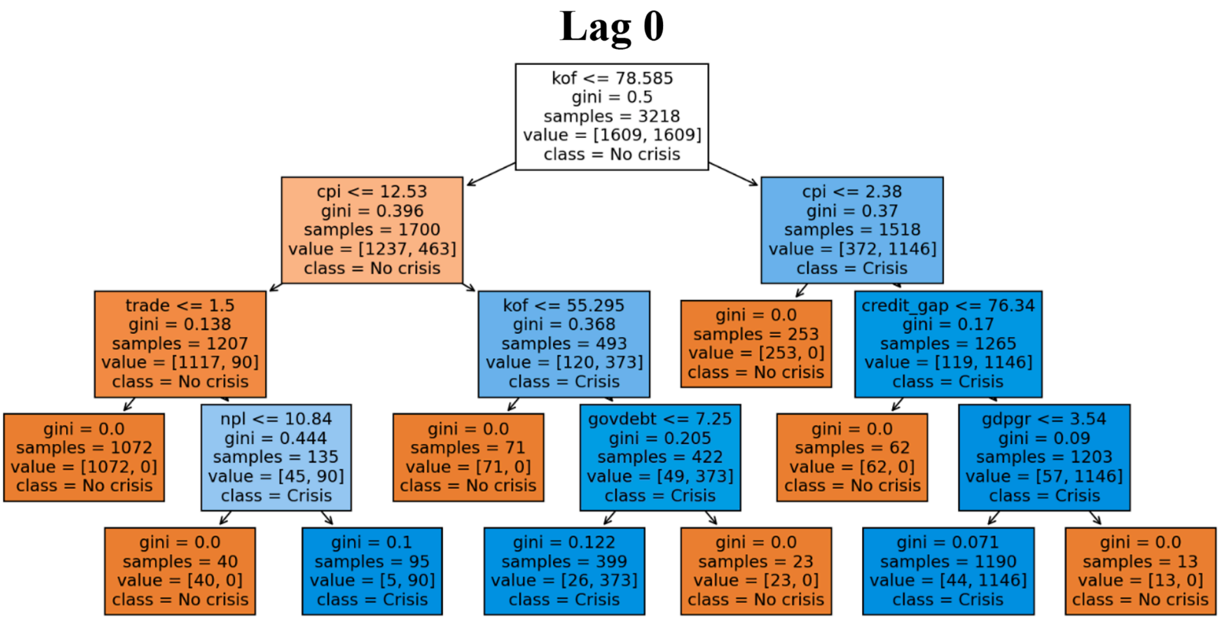
Appendix

Table 1
Descriptive statistics.

Variable	Definition of the variable	Mean	Std. Dev.
bank_crisis	=1 if banking crisis, =0 else	0.01	0.1
cur_crisis	=1 if currency crisis, =0 else	0.01	0.11
sov_crisis	=1 if sovereign crisis, =0 else	0	0.05
trade	=1 if trade sanctions, =0 else	0.2	0.71
arms	=1 if arms sanctions, =0 else	0.12	0.47
military	=1 if military sanctions, =0 else	0.07	0.39
financial	=1 if financial sanctions, =0 else	0.25	0.9
travel	=1 if travel sanctions, =0 else	0.16	0.64
other	=1 if other sanctions, =0 else	0.08	0.37
npl	Non-performing loans to assets	6.62	7.16
z	z-score	16.46	9.65
cost	Cost-to-income ratio	50.53	22.54
gdpgr	GDP growth	3.66	4.51
polity	Polity-V index	4.47	8.92
credit_gap	Credit-to-GDP gap	51.43	48.54
m2	Broad money to reserves ratio	3.76	8.4
cpi	Consumer price index	5.65	12.66
govdebt	Central government debt to GDP	27.79	62.75
kof	KOF globalization index	64.84	14.64
chin	Chinn-Ito Index of financial openness	0.54	1.58

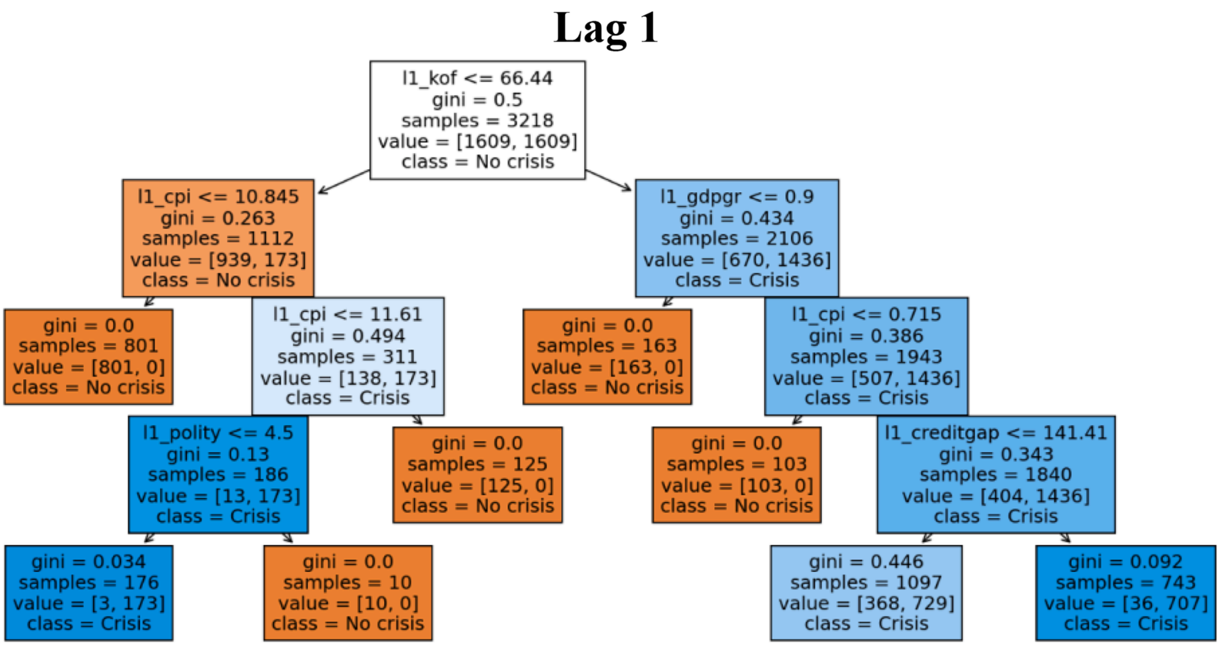
The table displays the descriptive statistics of the variables used in the estimations.

Panel A1. CART results for banking crises
Lag 0



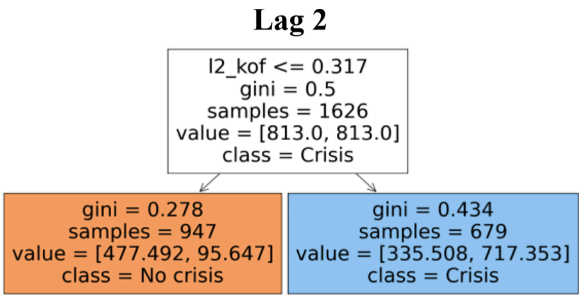
Accuracy = 0.85, ROC-AUC = 0.79, Sensitivity ratio= 0.71, Specificity ratio= 0.85

Lag 1



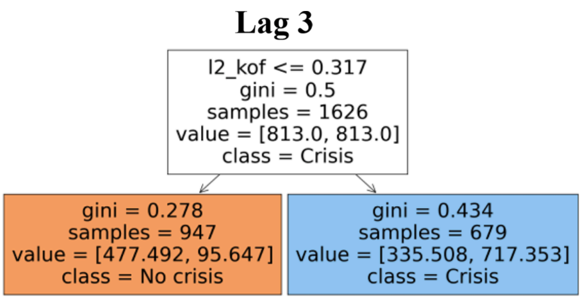
Accuracy = 0.81, ROC-AUC = 0.76, Sensitivity ratio= 0.71, Specificity ratio= 0.72

Lag 2



Accuracy = *0.66, ROC-AUC* = *0.70, Sensitivity ratio*= *0.71, Specificity ratio*= *0.65*

Lag 3

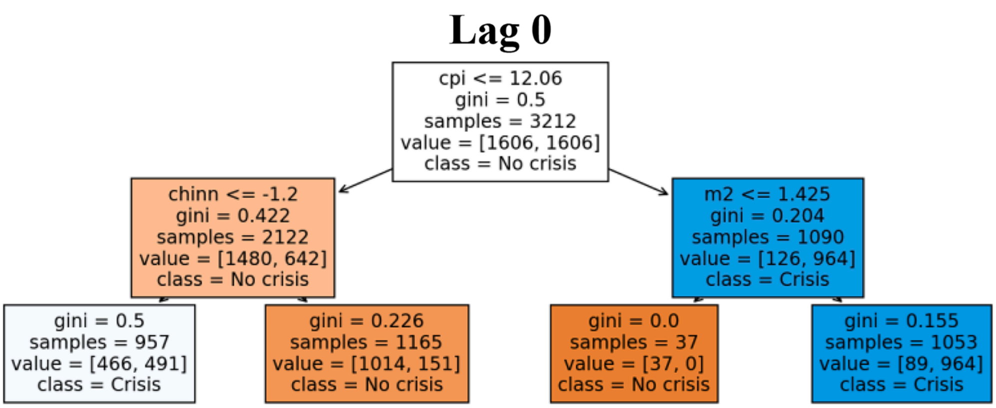


Accuracy = *0.73, ROC-AUC* = *0.87, Sensitivity ratio*= *1, Specificity ratio*= *0.72*

Note: Each node features the splitting variable with a corresponding threshold, the value of the Gini impurity index, number of observations initially classified into this node, number of observations splitted into crisis and non-crisis groups by a splitting variable and the final prediction for the node.

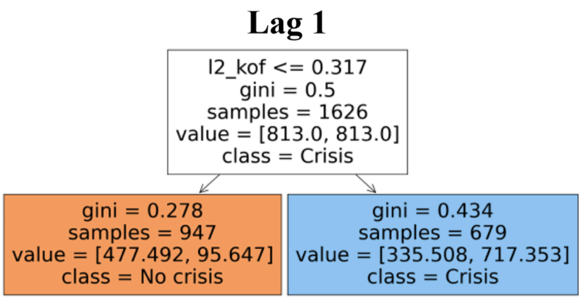
Panel A2. CART results for currency crises

Lag 0



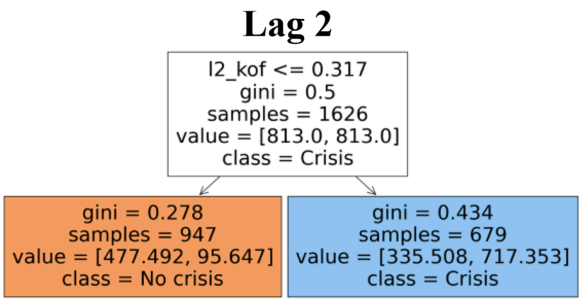
Accuracy = *0.73, ROC-AUC* = *0.87, Sensitivity ratio*= *0.63, Specificity ratio*= *0.72*

Lag 1



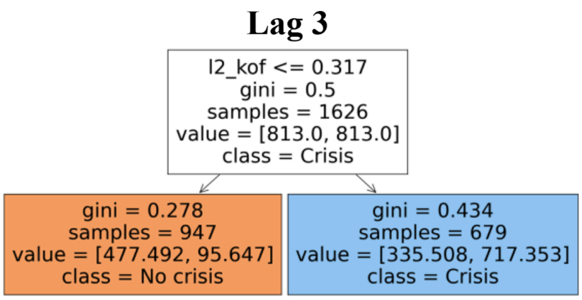
Accuracy = 0.60, ROC-AUC = 0.65, Sensitivity ratio= 0.63, Specificity ratio= 0.60

Lag 2



Accuracy = 0.60, ROC-AUC = 0.63, Sensitivity ratio= 0.63, Specificity ratio= 0.59

Lag 3

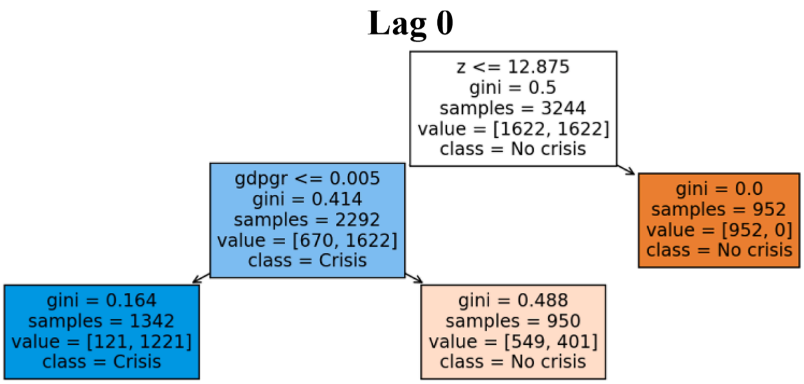


Accuracy = 0.73, ROC-AUC = 0.65, Sensitivity ratio= 0.63, Specificity ratio= 0.54

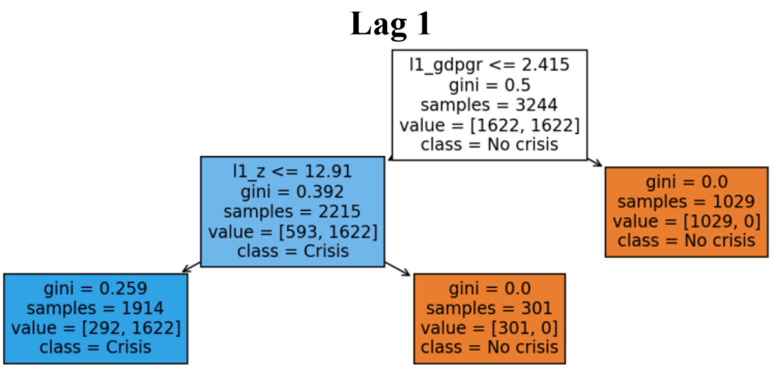
Note: Each node features the splitting variable with a corresponding threshold, the value of the Gini impurity index, number of observations initially classified into this node, number of observations splitted into crisis and non-crisis groups by a splitting variable and the final prediction for the node.

Panel A3. CART results for sovereign debt crises

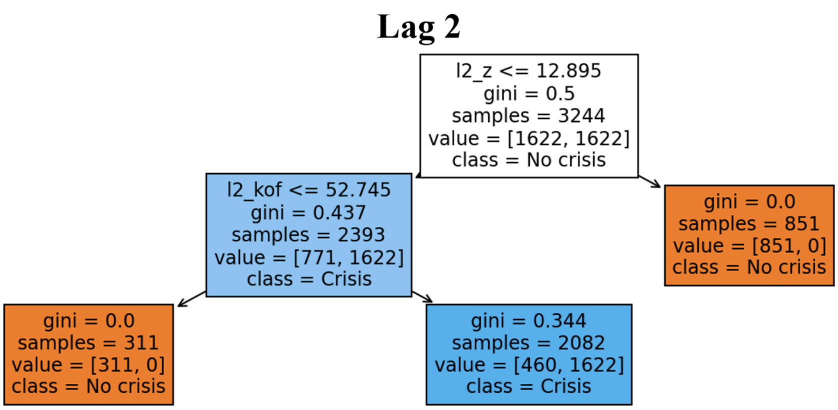
Lag 0



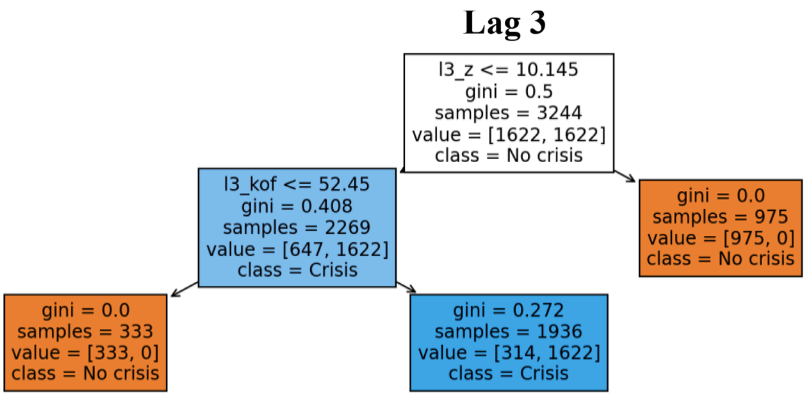
Accuracy = 0.79, ROC-AUC = 0.70, Sensitivity ratio= 0.5, Specificity ratio= 0.79
Lag 1



Accuracy = 0.86, ROC-AUC = 0.71, Sensitivity ratio= 1, Specificity ratio= 0.60
Lag 2



Accuracy = 0.86, ROC-AUC = 0.71, Sensitivity ratio= 0.5, Specificity ratio= 0.86
Lag 3



Accuracy = 0.91, ROC-AUC = 0.62, Sensitivity ratio= 0.5, Specificity ratio= 0.91

Note: Each node features the splitting variable with a corresponding threshold, the value of the Gini impurity index, number of observations initially classified into this node, number of observations splitted into crisis and non-crisis groups by a splitting variable and the final prediction for the node.

References

Afesorgbor, S.K., 2019. The impact of economic sanctions on international trade: how do threatened sanctions compare with imposed sanctions? Eur. J. Polit. Econ. 56, 11–26.

Aydın, S., Tunç, C., 2023. What is the most prominent reserve indicator that forewarns currency crises? Econ. Lett. 231, 111282.

Biglaiser, G., Lektzian, D., 2011. The effect of sanctions on US foreign direct investment. Int. Organ. 65 (3), 531–551.

Breiman, L., Friedman, J.H., Olshen, R.A., Stone, C.J., 1984. Classification and Regression Trees. Chapman & Hall/CRC, New York.

Crespo Cuaresma, J., Slacík, T., 2008. Determinants of currency crises: a conflict of generations? Focus Eur. Econ. Integr. 1, 126–141.

Dell'Ariccia, M., Ferreira, C., Jenkinson, N., Laeven, M., Martin, A., Minoiu, M., Popov, A., 2018. Managing the sovereign-bank nexus. ECB Working paper № 2177.

Duttagupta, R., Cashin, P., 2008. The anatomy of banking crises. IMF Working Papers, 2008(093).

Felbermayr, G., Kirilakha, A., Syropoulos, C., Yalcin, E., Yotov, Y., 2020. The global sanctions data base. Eur. Econ. Rev. 129, 103561.

Fiordelisi, F., Girardone, C., Minnucci, F., Ricci, O., 2020. On the nexus between sovereign risk and banking crises. J. Corp. Finance 65, 101717.

Galil, K., Hauptman, A., Rosenboim, R., 2023. Prediction of corporate credit ratings with machine learning: simple interpretative models. Finance Res. Lett. 58 (Part D), 104648.

Hatipoglu, E., Peksen, D., 2018. Economic sanctions and banking crises in target economies. Defense Peace Econ. 29, 171–189.

Kaminsky, G., Reinhart, C., 1999. The twin crises: the causes of banking and balance-of-payments problems. Am. Econ. Rev. 89 (3), 473–500.

Laborda, R., Laborda, J., 2017. Can tree-structured classifiers add value to the investor? Finance Res. Lett. 22, 211–226.

Laeven, L., Valencia, F., 2020. Systemic banking crises database II. IMF Econ. Rev. 68, 307–361.

Manasse, P., Roubini, N., 2009. Rules of thumb" for sovereign debt crises. J. Int. Econ. 78 (2), 192–205.

Morgan, T., Syropoulos, C., Yotov, Y., 2023. Economic sanctions: evolution, consequences, and challenges. J. Econ. Perspect. 37 (1), 3–30.

Peksen, D., Son, B., 2015. Economic coercion and currency crises in target countries. J. Peace Res. 52, 448–462.

Reinhart, C., Rogoff, K., 2009. This Time It's Different: Eight Centuries of Financial Folly. Princeton University Press.

Savona, R., Vezzoli, M., 2015. Fitting and forecasting sovereign defaults using multiple risk signals. Oxf. Bull. Econ. Stat 77 (1), 66–92.