

INTERNATIONAL MONETARY FUND

How to Assess Country Risk: The Vulnerability Exercise Approach Using Machine Learning

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ACKNOWLEDGMENTS

We are grateful for the support of this project by the iLab through the AI/ML Innovation Challenge and Catalyst series. We would also like to gratefully acknowledge the support from and the discussions with Michal Andrlé, Alberto Behar, Angana Banerji, Fabian Bornhorst, Eugenio Cerutti, Marcos Chamon, Kirpal Chauhan, Qianying Chen, Mali Chivakul, Federico Diaz Kalan, Florence Dotsey, Aquiles Farias, Vikram Haksar, Yuko Hashimoto, Niko Alfred Hobdari, Plamen Iossifov, Tetsuya Konuki, Miguel Lanza, Emilia Magdalena Jurzyk, Maxym Kryshko, Nan Li, Sandra Lizarazo, Albert Touna Mama, Jimmy McHugh, Alexis Meyer Cirkel, Chifundo Moya, Nkunde Mwase, Rajesh Nilawar, Liam O'Sullivan, Marijn Otte, Mamoon Saeed, Jasmin Sin, Shannon Staley, Fabian Valencia, Tristan Walker, Hans Weisfeld, Jason Weiss, and Weijia Yao.

Cataloging-in-Publication Data
Joint Bank-Fund Library

Names: International Monetary Fund.

Title: How to Assess Country Risk: The Vulnerability Exercise Approach Using Machine Learning

Other titles: Technical Notes and Manuals (International Monetary Fund)

Series/volume #: TNM/21/03

Description: Washington, DC : International Monetary Fund | Periodic | Some issues also have thematic titles.

Classification: LCC HC10.W79
HC10.80

ISBN: 978-1-51357-421-9

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JEL Classification Numbers:	C14, C36, C38, C52, C53, E32, E37, F32, F47, G01, H63
Keywords:	Risk Assessment, Supervised Machine Learning, Prediction, Sudden Stop, Exchange Market Pressure, Fiscal Crisis, Debt, Financial Crisis, Economic Crisis, Economic Growth
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CONTENTS

Executive Summary	5
Introduction	7
Machine Learning and Crisis Forecasting	9
Models and Estimation Strategy	11
Communicating Results	14
External Sector Model	17
Fiscal Sector Model	26
Financial Sector Model	32
Real Sector Model	38
Conclusion and Next Steps	45
References	46
Annexes	
I. Signal Extraction Method	50
II. From Decision Trees to a Random Forest	51
III. Beyond Random Forests: Balanced Forest and Boosting	53
IV. Predicting Out-of-Sample Performance: Cross Validation	55
V. Comparing Classifiers: Area Under the Curve (AUC)	57
VI. Assigning the Blame: Shapley Values	59
VII. Filling in the Gaps: Dealing with Missing Data	61
VIII. Fiscal Sector Explanatory Variables	63

Figures

1. Risk Architecture at the IMF	7
2. Fiscal Crisis Risk – Country A, 2019	13
3. Contribution to Risk Index	14
4. Distribution of Variable with Largest Risk Contributions	15
5. Countries with a Similar Financial Sector Risk Profile with Ireland in 2005	16
6. Frequency of Sudden Stops	17
7. Frequency of EMP Events	18
8. External Sector Model Performance: SSGI	21
9. External Sector Model Performance: EMP Events	21
10. SSGI Model Variable Importance	22
11. EMP Model Variable Importance	23
12. Historical Risk Indices Over Time	24
13. External Risk Interactions	25
14. External Sudden Stop Index and the Asian Financial Crisis, Selected Countries	25
15. Countries with Fiscal Crises, 1980-2017	27
16. Fiscal Sector Model Performance	28
17. Fiscal Model Variable Importance	29
18. Fiscal Risk in Greece, 2009	30
19. Bank Crisis History and Frequency	31
20. Financial Sector Model Performance	34
21. Financial Model Variable Importance	34
22. Historical Evolution of Average Risk Index	35
23. Global-Local Variable Interaction in Financial Sector Model	36
24. Financial Crisis Risk Index, Iceland and Ireland, 2005 and 2007	37
25. Real Sector Crisis History	39
26. Real Sector Model Performance	41
27. Real Model Variable Importance	42
28. Nonlinear Interactions in Real Sector Model	43
29. Crisis Risk Indices in Four Sectors, Ethiopia and Greece	44

Tables

1. External Crisis: Explanatory Variables	20
2. Definitions	26
3. Financial Crisis: Explanatory Variables	33
4. Real Crisis: Explanatory Variables	40

EXECUTIVE SUMMARY

The IMF's Vulnerability Exercise (VE) is a cross-country exercise that identifies country-specific near-term macroeconomic risks. As a key element of the Fund's broader risk architecture, the VE is a bottom-up, multi-sectoral approach to risk assessments for all IMF member countries. Assessments reflect the judgement of country teams informed by consistent, cross-country quantitative models as well as country-specific context.

The VE modeling toolkit is regularly updated in response to global economic developments and the latest modeling innovations. Earlier models evolved organically, assessing advanced economies, emerging markets, and low-income countries separately and looking at different types of risks. The new generation of models presented here closes gaps in risk and country coverages from previous models, while improving consistency and comparability of risk assessments across countries.

The new generation of VE models presented here leverages machine-learning (ML) algorithms. Macroeconomic risk assessment is a challenging task: crises are infrequent and almost always involve some elements of surprise. They tend to feature interactions between different parts of the economy and non-linear relationships that are not well measured in "normal times." ML tools can often better capture these relationships. They can also be more robust to outliers, noise, and the diversity of experiences across countries.

The performance of machine-learning-based models is evaluated against more conventional models in a horse-race format. The models assess the near-term risk of a crisis in the external, financial, fiscal, and real sectors. In each sector, rigorous performance metrics are used to compare new tools against traditional approaches. It turns out that random forest-based models, which are popular modern ML methods that average over many decision trees, outperform other options in most cases. In other cases, the signal extraction approach, a robust non-parametric method designed for macro-crisis detection, performs best. These winning models represent a new generation of models at the core of the VE.

The paper also presents direct, transparent methods for communicating model results. ML techniques can sometimes appear to be a black box due to their complexity and infrequent (though rapidly growing) use in economics. Communication tools, developed to inform country teams about the model assessments, help take the last step from predicting to informing.