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Financial Hazard Map: Financial Vulnerability Predicted by a Random Forests Classification Model

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Abstract: This study develops a systematic framework for assessing a country's financial vulnerability using a predictive classification model of random forests. We introduce a new indicator that quantifies the potential loss in bank assets and measures a country's overall vulnerability by aggregating these indicators across the banking sector. We also visualize the degree of vulnerability by creating a Financial Hazard Map that highlights countries and regions with underlying risks in their banking sectors.

Keywords: financial hazard map; random forests; early warning system; bank failure

1. Introduction

The severe economic consequences of the global financial crisis of 2008–2009 highlighted the importance of crisis prevention and sparked a renewed interest in early warning systems (EWSs). An EWS aims to detect potential vulnerabilities in a financial system that could trigger a system-wide crisis. A reliable EWS provides useful guidance for policy-makers to activate macro-prudential policy in an effective and timely manner. The International Monetary Fund (IMF) [1] and the Committee on the Global Financial System [2] provide a comprehensive discussion of the operational aspects of the macro-prudential policy. After Frankel and Rose [3] and Kaminsky et al.'s [4] early contributions, researchers have made considerable efforts to develop a consistently useful EWS for various types of crises.

Kaminsky et al. [4] proposed the popular signaling approach, which Alessi and Detken [5] recently used. This approach seeks to identify the threshold values for individual indicators that signal crises, and thus trigger an early warning when the pre-defined threshold for the pre-selected indicator is breached. A popular indicator common in these studies is the credit-to-GDP (Gross Domestic Product) ratio, which is a key indicator signaling credit booms. However, this signaling approach has a shortcoming given that, as a univariate approach, the decision would rely on only a single factor, which can send a misleading signal.

Another conventional approach from the EWS literature is estimating the multivariate probit and logistic regressions, which relate the probability of a crisis to a set of explanatory variables, such as current account balance, real exchange rates, credit growth, and fiscal balance [6–10]. Despite its popularity, the conventional approach has certain limitations. For one, researchers must pre-select explanatory variables from a wide range of economic indicators based on some prior information. For another, the logistic regression does not readily allow for non-linear or threshold effects of explanatory variables. More generally, linear regressions often perform poorly in terms of prediction performance relative to newer machine learning models [11]. Linear regressions may work well for small datasets but they are not readily scalable to larger datasets.

Ghosh and Ghosh [12] and Frankel and Wei [13] employed a decision tree method that uses a sequence of splitting rules to segment the space of explanatory variables. Hastie et al. [11] and James et al. [14] provide details of tree methods, including decision trees and random forests. At each node of a tree, the sample is split into two sub-branches according to the threshold value of an explanatory variable. For classification trees, either the Gini index or the cross entropy is used to evaluate the quality of a split. A smaller value of these indices indicates that the node is purer, and thus contains more observations from a single class. The process is repeated until a stopping criterion is reached, such as the minimum number of observations at each node. Each terminal node at the bottom of the tree provides a class prediction for a given observation. Whereas linear logistic regressions models require a handcrafted selection of explanatory variables to obtain reasonable early warning performance, the decision tree systematically learns important variables, performs better in early warning, and allows for non-linear effects. Although a decision tree is simple and provides explanatory and intuitive decision rules, it suffers from high variance (i.e., a small change in the data can cause a large change in the financial tree), so is likely to suffer over-fitting problems. This is largely owing to the fact that the values of the thresholds depend heavily on the values of the training observations.

With an increased opportunity to gain access to larger datasets, exploring the significant scope for economic modeling and analysis for a more flexible approach has become popular with data scientists [15,16]. In this study, we take advantage of the advancements in predictive modeling techniques of machine learning to build an EWS, and develop a systematic framework to assess and visualize a country's financial vulnerability. The main contributions of our study are three-fold. First, our study differs from previous ones in that we used a novel machine-learning technique known as random forests to construct an EWS to predict bank failures (random forests EWS). Random forests are a variant of decision trees that significantly improve prediction accuracy by combining a large number of trees using random input selection [17]. Second, we introduce a new indicator that quantifies the expected potential loss in bank assets computed using the prediction of the random forests EWS. To assess a country's overall financial vulnerability, we aggregate individual banks' expected potential asset losses across the domestic banking sector. Finally, we visualize the degree of a country's financial vulnerability by creating a Financial Hazard Map that highlights countries and regions with significant risks in their underlying banking sectors. Our work is similar to that of Tanaka et al. [18], but differs by a few points. Our paper provides a financial analysis of the finance sector, whereas the interest of Tanaka et al. focused on the industrial sector. Furthermore, we propose a novel indicator to assess the overall financial vulnerability of each country.

We chose random forests (RF) for three reasons. First, RF can significantly improve prediction accuracy by building a large number of decision trees on bootstrapped training samples—a technique known as ensemble learning. Random forests also circumvent the over-fitting problem by adding randomness to the tree building process, and thus reducing correlations among trees; hence, it performs well with out-of-sample data. Second, random forests can better handle a large dataset as multiple trees can be trained in parallel efficiently with a very simple hyper-parameter setting. The model can be built by merely setting the number of trees. Finally, RF provide the importance measurement, which can be used for certain levels of causality inference. Whereas various application areas use random forests, including computer vision and bioinformatics, its application to economics remains limited. Tanaka et al. [19] used random forests to predict bank failure in OECD member countries.

Another important feature of our study is the use of bank-level financial statements to predict bank failure using the random forests EWS built from a large dataset of more than 15,000 banks globally. As previous studies typically used macroeconomic indicators to predict currency and financial crises, the recent literature indicates that the state of bank financial statements can explain differences in performance across banks during financial crises [20,21]. Moreover, previous studies often defined a crisis as an event in which the values of preselected indicators exceed predetermined thresholds. Consequently, the prediction performance significantly depends on the choice of threshold. We define the event of a bank failure as the change in a bank's status from active to inactive (i.e., bankrupt, in liquidation, or dissolved) based on the information provided by the Bureau Van Dijk Bankscope. By doing so, we wanted to minimize arbitrariness, and thus reduce the possible bias in prediction.

The remainder of the paper proceeds as follows. Section 2 describes the methodology and data of building the random forests EWS. Section 3 introduces a new indicator that quantifies the expected potential losses in bank assets. We present the assessment of a country's financial vulnerability and visualize it by creating a Financial Hazard Map. Section 4 provides our conclusions.

2. Materials and Methods

In this study, we considered the task of building an EWS as a classification problem to identify a bank's status (i.e., active or inactive) based on the underlying financial conditions. Drawing on insights from the extensive literature on corporate bankruptcy predictions, we used information about individual banks' financial statements as predictors to build models. Altman [22] provides an early contribution to the literature. In contrast to existing studies that are more concerned with identifying the key predictors of bankruptcy, we prioritized improving the prediction accuracy. To this end, we used random forests that tend to perform better in terms of prediction accuracy than conventional methods, such as logistic regressions, which have been widely used in previous studies.

2.1. Major Features of Random Forests

Random forests are a variant of decision trees, which overcome the over-fitting problem by building multiple trees and combing the results of these trees [17], effectively forming forests. Each tree in a random forest is built using randomly selected data samples and/or randomly selected input variables from the original data to split each node. After generating a large number of trees, the model votes for the most popular class. A single-tree classifier tends to have only marginally better accuracy than a random choice of class. However, by combining a large number of trees using random input selection, random forests can produce a powerful model.

Breiman et al. [17] constructed such trees using the Gini index criterion, which measures the best split criterion based on the impurity of each node. The algorithm aims to select the optimal splitting variable and the corresponding threshold value by making each node as pure as possible. Suppose M_n is the number of pieces of information reaching node n and M_n^i is the number of data points belonging to class C_i, the Gini index, GI_n, of node n is obtained using Equation (1):

$$GI_n = 1 - \sum_{i=1}^{K} \left(p_n^i\right)^2, \text{ where } p_n^i = \frac{M_n^i}{M_n} \tag{1}$$

A smaller Gini index value for node n represents greater purity, which implies that the node contains more observations from a single class. Hence, a decreasing Gini index is an important criterion when splitting a node.

In comparison to single-tree modeling, random forests have several desirable features [17,23]. First, random forests perform better in terms of classification accuracy by building a large number of trees instead of only a single tree. Each tree is built using randomly selected data samples and randomly selected input variables from the original data to split each node. After generating a large number of trees, they vote for the most popular class. A single-tree classifier tends to have only marginally better accuracy than a random choice of class. However, by combining a large number of trees using random input selection, random forests can improve accuracy. Second, random forests provide better generalization abilities and are robust to over-fitting. Hence, RF may have better out-of-sample accuracy when using a random selection of input variables to split each node and combining the results of multiple trees yields error rates that compare favorably to alternative methods and are more robust with respect to noise. Third, random forests can better handle large datasets as multiple trees can be efficiently trained in parallel. Finally, random forests provide a measure for the relative contribution of each variable to generate a prediction. These variable importance measures help identify the variables that are important for distinguishing between active and inactive banks, and thus for predicting bank failure.

2.2. Data

We sourced our data for bank financial statement indicators from Bankscope. The advantage of using this data source is that it provides a broad coverage of banks with standardized data formats across countries. We used 48 indicators derived from the Summary Analytics category classified into four groups: profitability ratio, capitalization, loan quality, and funding (Appendix B). Our sample included 23,455 commercial banks, saving banks, and cooperatives incorporated in 198 countries and regions. The training set included annual observations of the latest available financial statements for each bank up to 2014. We defined a bank failure event as the change in a bank's status from active to inactive (i.e., bankrupt, in liquidation, or dissolved) as reported by Bankscope. We assumed that the latest available financial statements for active banks had sound financial status and inactive banks had unsound financial status. We then systematically identified patterns distinguishing the differences by random forests.

As there were fewer inactive banks (7294 banks), we selected the largest 7294 active banks in terms of total assets to match the number of inactive banks. We also selected the smallest 7294 active banks to build a more flexible model to prevent a bias toward larger banks. To avoid model bias created by an imbalanced training set, we evened out the sample sizes of active and inactive banks by doubling the sample size of inactive banks by duplicating each observation. In addition, we eliminated variables if more than 50% of its values were missing (7294 $\times$ 2 biggest and smallest active banks + 7294 inactive banks). Thus, we eliminated 6 variables and used 42 variables for experiments. We used the random forests and caret packages in the R software package to train and evaluate our models. Figure 1 illustrates the model building process for the random forests EWS. Appendix C reports the classification accuracy of the random forests EWS.

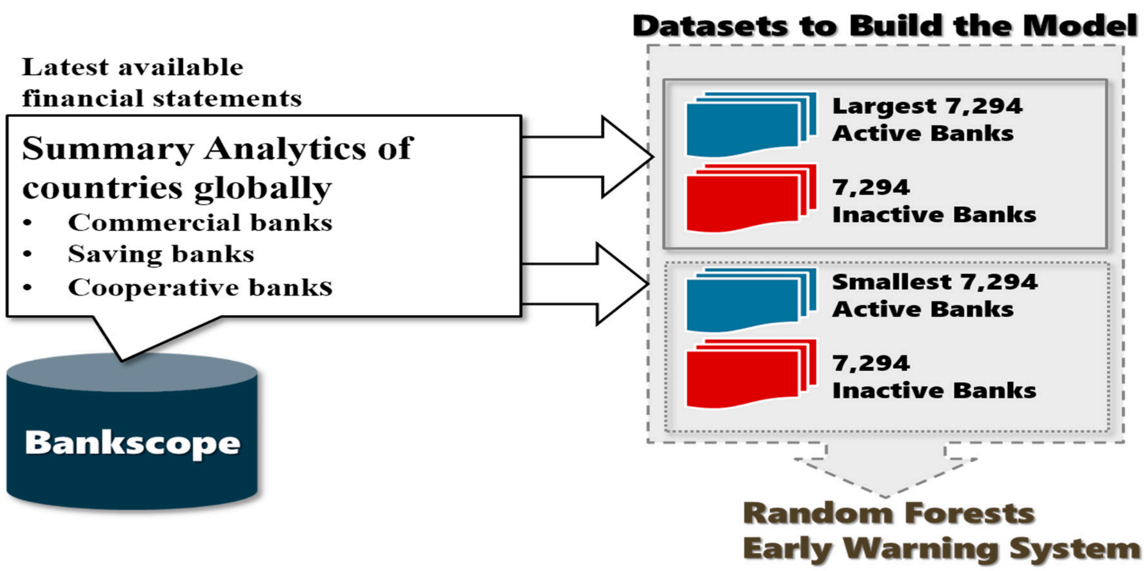

Figure 1. Model building process of random forests early warning system (EWS).

3. Results

3.1. Variable Importance Measures

A useful property of random forests is that it provides variable importance measures that help identify the most important variables for distinguishing between active and inactive banks. Hence, RF should provide some clues to the underlying causes of bank failures. For classification trees, we obtained the variable importance measures from each variable's contribution to the reduction in the Gini index. The Gini index is a common measure of the degree of inequality in income distribution. The smaller the value of the index, the more equal the society.

In our random forests algorithm, the Gini index is the measure for the purity of each node. A smaller value of the Gini index represents a purer node, which implies that the node contains more observations from a single class. The goal of the algorithm was to make each node as pure as possible by selecting the optimal splitting variable and the corresponding threshold value. Therefore, we calculated variable importance by summing the total reduction in the Gini index by splits over a given variable, averaged over all bagged trees.

Figure 2 illustrates the variable importance measures as the mean decrease in the Gini index for each variable. Considering this model, we identified the following indicators as the top four predictors: interest expense/average interest-bearing liabilities, interest income on loan/average gross loans, interest expense on customer deposits/average customer deposits, and interest income/average earning assets. The importance measure for the first indicator was by far the largest. These top four indicators fall into the profitability ratio category. In contrast, the importance measures for the other categories of indicators, that is, capitalization, loan quality, and liquidity are much smaller. The results indicate that bank profitability has the most important impact on the probability of bank failure.

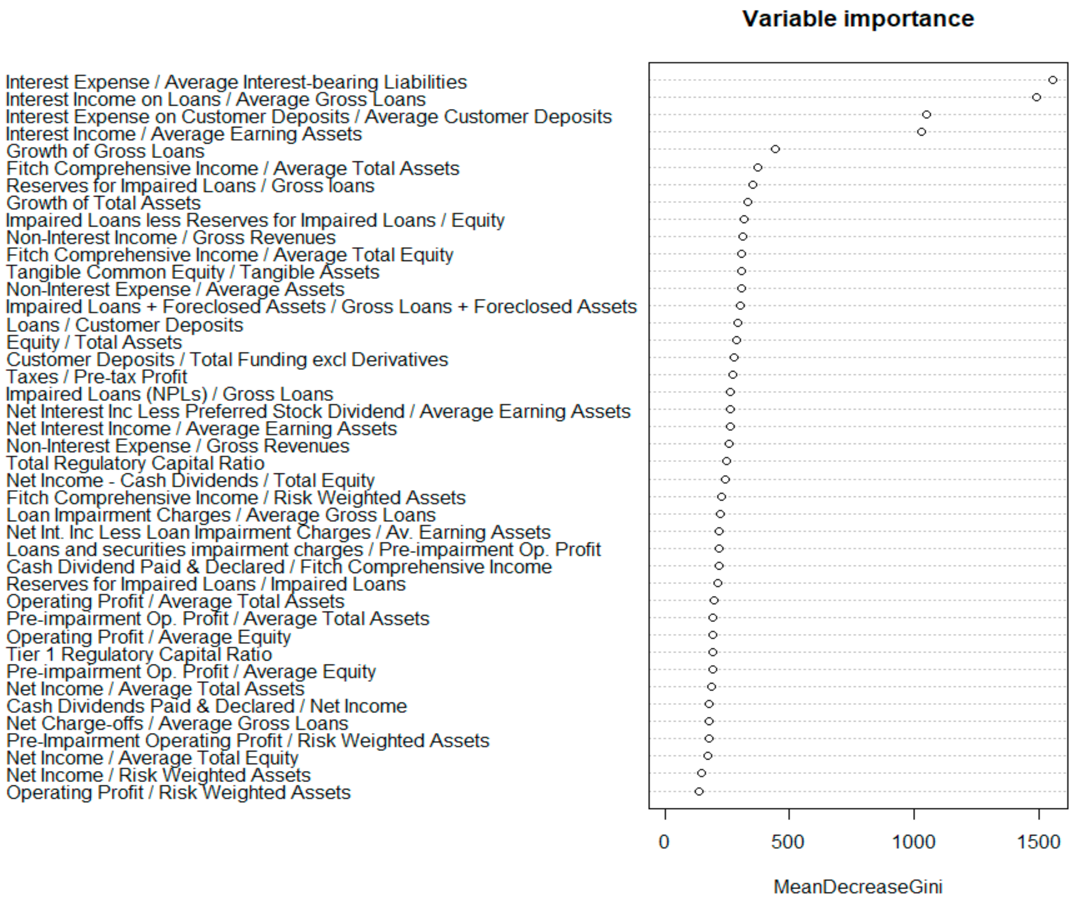

Figure 2. Variable importance measures of random forests.

We show the experimental result of a single decision tree in Figure 3 for comparison. Though a single tree selects similar criteria to distinguish between active and inactive banks, it does not perform as well as random forests. This is due to the fact that the random forests model produces a more flexible model as it produces multiple trees to analyze different patterns in the data, whereas a single tree only produces one set of rules for a classification decision.

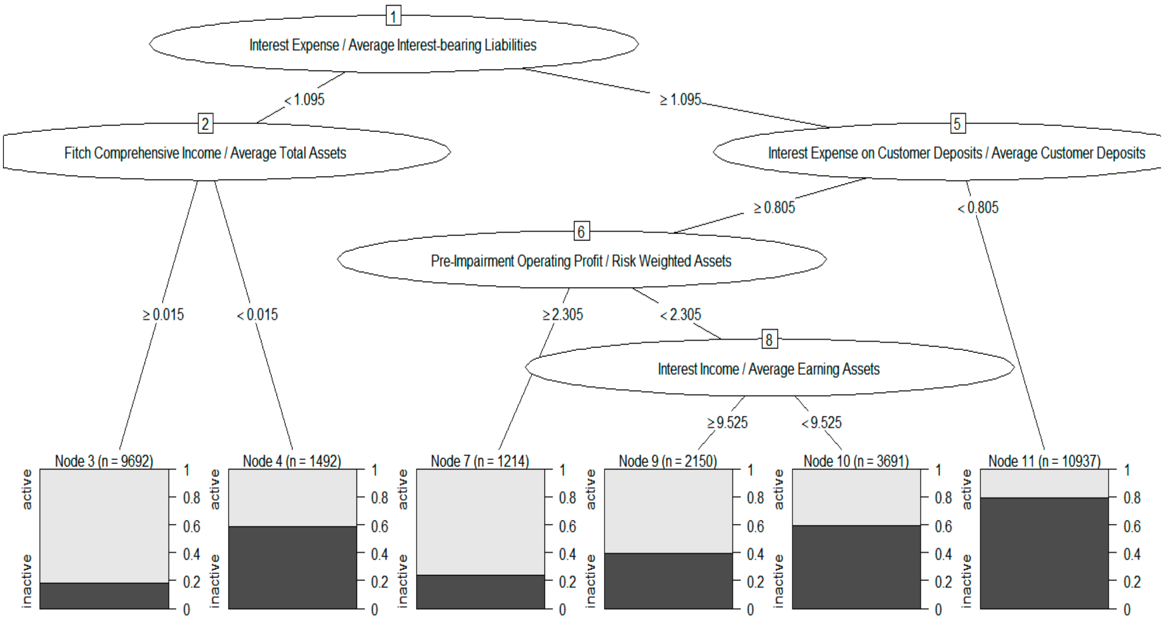

Figure 3. Plot of a tree model.

3.2. New Indicator for the Expected Potential Asset Loss

We introduce a new indicator to assess the degree of financial vulnerability using the prediction of the random forests EWS. We used the 2014 financial statement data to predict the probability of bank failure. We define the expected potential asset loss of a bank as follows:

$$\mathrm{EPAL}_{i,j} = \mathrm{P}_{i,j} \times \text{Total Assets}_{i,j}, \tag{2}$$

where $\mathrm{EPAL}_{i,j}$ denotes the expected potential loss in bank i in country j, $\mathrm{P}_{i,j}$ denotes the probability of failure for bank i in country j given by the random forests EWS prediction, and Total $\text{Assets}_{i,j}$ denotes the value of total assets of bank i in country j. To measure a country's overall financial vulnerability, we aggregate the value of $\mathrm{EPAL}_{i,j}$ across the domestic banking sector. Given that we used consolidated financial statement data, all the expected potential loss of multinational banks was counted as losses in the country where the headquarters of these banks were located. We acknowledge that this is the limitation of our work and consider overcoming this limitation as our future task. Hence, the country-level expected potential loss in the domestic banking sector denoted by EPAL_j is given by:

$$\mathrm{EPAL}_j = \sum\nolimits_i \mathrm{EPAL}_{i,j}. \tag{3}$$

To gauge the impact of the expected potential asset loss on the domestic banking sector and economic activities, we calculated the share of EPAL_j in the total assets of the domestic banking sector and in nominal GDP. Table 1 summarizes the results.

The left column of the table ranks 50 countries in terms of their share in banking sector assets. The ranking indicates that Suriname, Grenada, Denmark, Gabo, and Guatemala are the five most vulnerable countries in the sense that the impact of the expected potential loss on the domestic banking sector can be relatively large. Thus, these countries have a relatively high risk of a system-wide banking crisis.

The right column of the table ranks countries in terms of the share in nominal GDP. The ranking indicates that the Palestinian Territories, Luxembourg, Cyprus, Denmark, and France are the five most vulnerable countries in the sense that the impact of the expected potential asset loss on domestic economic activities could be relatively large. This is particularly the case if the assets of banks with high probability of failure consist primarily of domestic loans and investments.

Table 1. Top 50 countries in terms of the shares of expected potential asset loss based on 2014 financial statements.

Share of Expected Potential Asset Loss in Domestic Banking Sector		Share of Expected Potential Asset Loss in Nominal GDP	
SURINAME	37.92%	PALESTINIAN TERRITORIES	137.53%
GRENADA	31.00%	LUXEMBOURG	135.54%
DENMARK	28.14%	CYPRUS	100.92%
GABON	28.06%	DENMARK	81.80%
GUATEMALA	27.33%	FRANCE	71.26%
VENEZUELA	25.65%	VENEZUELA	67.12%
SENEGAL	25.30%	PORTUGAL	58.03%
NEPAL	24.41%	LEBANON	56.36%
UZBEKISTAN	24.41%	JORDAN	56.25%
KYRGYZSTAN	24.31%	BAHRAIN	52.90%
CAMEROON	24.04%	SPAIN	50.81%
LESOTHO	23.54%	MAURITIUS	50.56%
EL SALVADOR	23.25%	UNITED KINGDOM	41.92%
DOMINICA	23.00%	SWITZERLAND	39.83%
ROMANIA	22.44%	AUSTRIA	38.16%
THAILAND	21.48%	HONG KONG	37.43%
HUNGARY	20.99%	GERMANY	37.28%
MONTENEGRO	20.74%	NETHERLANDS	36.94%
ETHIOPIA	20.51%	BAHAMAS	34.16%
ARGENTINA	20.38%	SAINT KITTS AND NEVIS	32.75%
LIBERIA	19.95%	THAILAND	31.86%
TUNISIA	19.81%	BELGIUM	31.19%
LIECHTENSTEIN	19.72%	FINLAND	30.61%
BOSNIA AND HERZEGOVINA	19.66%	SAN MARINO	30.59%
COTE D'IVOIRE	19.01%	NEW ZEALAND	28.96%
PARAGUAY	18.75%	PANAMA	28.10%
SERBIA	18.50%	GRENADA	27.02%
MADAGASCAR	18.22%	ITALY	25.76%
BOLIVIA	18.17%	GREECE	23.50%
PORTUGAL	18.17%	MOROCCO	21.80%
REPUBLIC OF KOREA	18.09%	AUSTRALIA	21.56%
SAINT KITTS AND NEVIS	17.99%	CHILE	20.94%
HONDURAS	17.96%	IRELAND	20.55%
BELIZE	17.81%	NEPAL	19.99%
PERU	17.30%	CROATIA	19.43%
AUSTRIA	17.30%	ICELAND	18.82%
JORDAN	17.27%	CAPE VERDE	18.66%
MAURITIUS	17.13%	GUATEMALA	17.61%
UKRAINE	17.05%	REPUBLIC OF KOREA	17.19%
CAPE VERDE	17.03%	EL SALVADOR	17.05%
TURKMENISTAN	16.96%	ANTIGUA AND BARBUDA	17.03%
NEW ZEALAND	16.70%	SWEDEN	16.97%
MALI	16.15%	CANADA	16.74%
CROATIA	15.97%	HUNGARY	16.69%
CHILE	15.60%	DOMINICA	16.46%
BRUNEI DARUSSALAM	15.33%	HONDURAS	16.04%
ARMENIA	15.30%	BARBADOS	15.89%
DOMINICAN REPUBLIC	15.04%	SURINAME	15.52%
BAHRAIN	14.89%	VIETNAM	15.34%
ECUADOR	14.84%	TUNISIA	15.23%

Interestingly, many Organisation for Economic Co-operation and Development (OECD) countries, including European countries, at the top of the list. This may indicate that these countries have not recovered fully from the major financial crises, notably, the global financial crisis of 2008–2009 and the European debt crisis of 2010–2013, or new financial risks may be looming. Given the relatively large size of their domestic banking sectors, these countries can be the epicenter of cross-border financial spillovers by withdrawing overseas loans and investments in the face of financial difficulties.

In Figure 4, we create a scatter plot of the vulnerability measures reported in Table 1. The combination of higher values of these measures in a particular country implies greater financial vulnerability. The figure clearly indicates that Denmark and Venezuela stand out in terms of both measures, signaling significant risks. The bold horizontal and vertical lines indicate the medians of these measures; the shadows indicate the first quartiles. The medians of the share of $EPAL_j$ in the banking sector assets and nominal GDP are 11.60% and 7.85%, respectively. The level of these medians indicates the overall vulnerability of the global banking sector, with a significant increase in signaling financial risks. Notably, our vulnerability measure raises a red flag for potential trouble, but it does not identify the causes or the likely outcomes of the trouble. However, we believe that these measures are useful for spotting vulnerabilities, and thus encouraging regulators and investors to take preemptive actions.

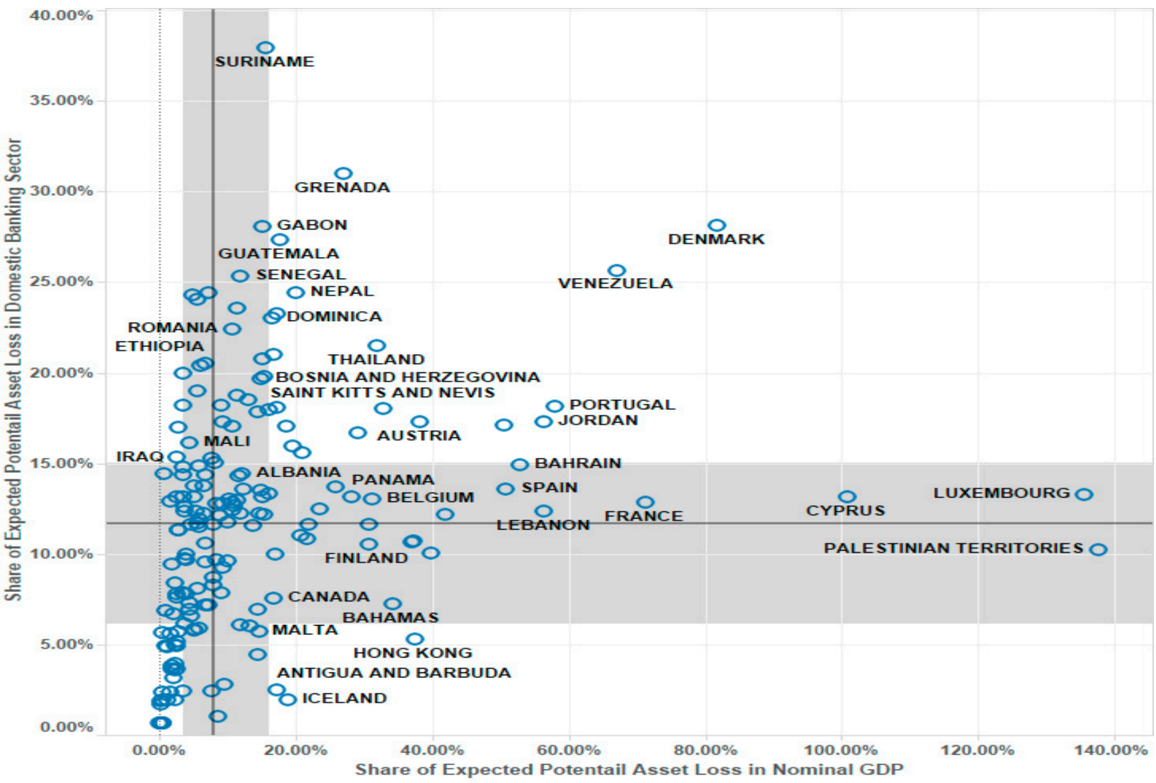

Figure 4. Scatter plot of country vulnerabilities.

In Appendix A, we summarize the predicted bank failures for each country for 2014. The table shows the number of banks and the sum of assets held by the banks for each category of predicted probability of failures with a 10-percentage-point interval.

3.3. Financial Hazard Map

Finally, we visualized the degree of a country's financial vulnerability by creating a Financial Hazard Map. Corresponding to each definition of vulnerability in Table 1, we present two types of maps. Figure 5 shows the share of $EPAL_j$ in the assets of domestic banking sectors. The areas that are darker red indicate a higher degree of vulnerability in terms of the impact of the expected potential asset loss on the domestic banking sector. Figure 6 shows the share of $EPAL_j$ in nominal GDP. Darker red areas indicate a higher degree of vulnerability in terms of the impact of the expected potential asset loss on domestic economic activities.

The Financial Hazard Map highlights countries and regions with significant vulnerability in their underlying banking sector. The darker red areas correspond to the top 50 countries listed in Table 1. The map provides a clear and understandable assessment of financial vulnerability in particular countries and regions. It also shows the geographical distribution of financial risk and the danger of potential contagion for neighbors of high vulnerability areas.

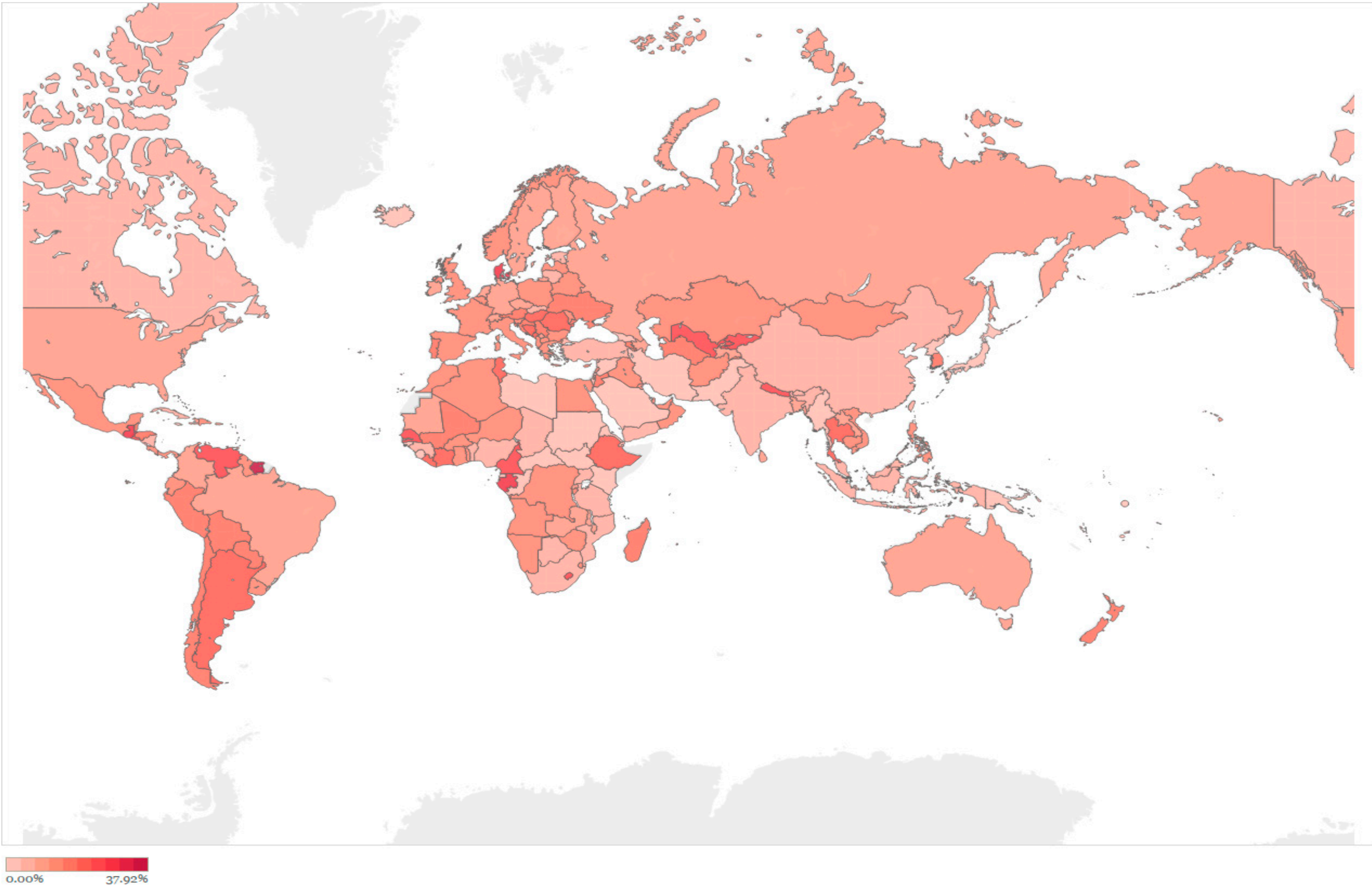

Figure 5. Impact of expected potential asset loss on the banking sector.

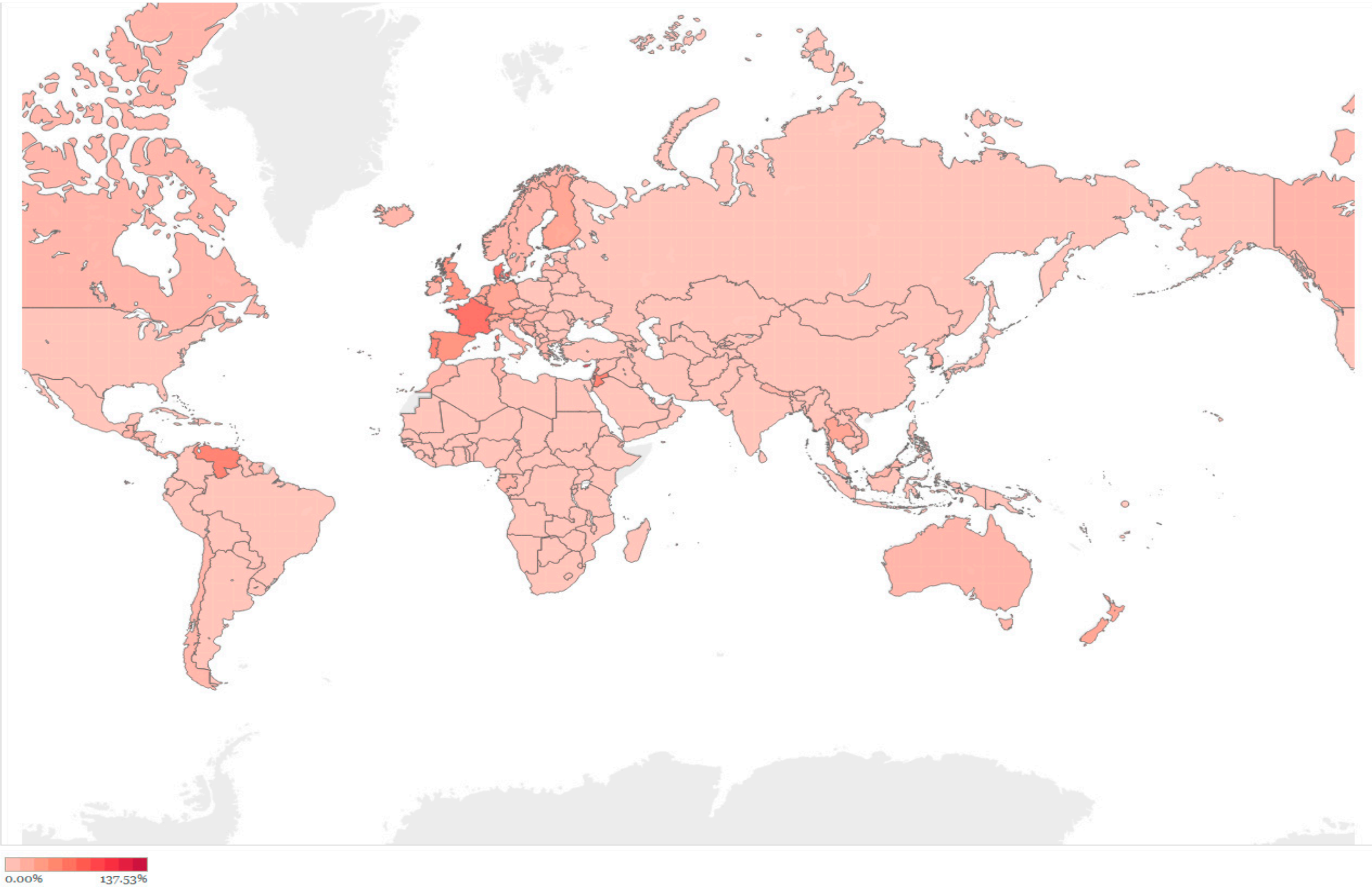

Figure 6. Impact of expected potential asset loss on economic activities.

4. Conclusions

We developed a systematic framework for assessing and visualizing a country's financial vulnerability. We employed a novel machine-learning approach known as random forests to construct an EWS to predict bank failures and introduced a new indicator that quantifies the expected potential loss in bank assets computed based on the random forests EWS prediction. We assessed the financial vulnerability of each country by aggregating individual banks' indicators across the banking sector. To gauge the impact of expected potential asset loss, we calculated the shares in the banking sector assets and nominal GDP. We identified countries and regions with high vulnerability in terms of these shares. Furthermore, we visualized the degree of a country's financial vulnerability by creating a Financial Hazard Map. We demonstrated the usefulness of the Financial Hazard Map in spotting vulnerable countries and regions and understanding the geographical distribution of risk.

We hope that the Financial Hazard Map will prove useful for both policy-makers and private investors in detecting potential risk, and thereby prompting precautionary actions. Our framework of assessing financial vulnerability is simple, and therefore readily applicable to other types of risk analysis. A future task may be to develop a dynamic framework that allows for an assessment of contagion risks between banks and countries potentially in trouble, taking account of country-specific macroeconomic and institutional factors.

Author Contributions: S.H. and T.K. conceived and designed the experiments; K.T. performed the experiments; S.H., T.K. and K.T. analyzed the data; K.T. contributed reagents/materials/analysis tools; K.T. wrote the paper.

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Appendix A

Numbers and assets of banks for each category of bank failure probabilities.

	Number of Banks										Total Asset(millions of US dollar)										Nominal GDP (billions of US dollar)
	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	
AFGHANISTAN	3	2	2	3	1					11	1,832	1,485	467	572	341					4,697	20.44
ALBANIA	2	8	2		1					13	1,361	8,371	932		385					11,049	13.30
ALGERIA	5	4	6	1	1					17	61,900	6,990	43,402	278	413					112,983	213.52
ANDORRA	3	1								4	11,106	1,566								12,672	
ANGOLA	8	2	4	1						15	31,675	8,428	12,464	1,965						54,532	126.78
ANGUILLA	2									2	644									644	
ANTIGUA AND BARBUDA	8		1	1						10	8,012		113	416						8,541	1.25
ARGENTINA	23	25	12	5						65	15,688	70,364	68,799	6,694						161,545	544.73
ARMENIA	8	3	2	1	2					16	3,531	731	716	206	671					5,855	11.64
ARUBA	1	1								2	580	1,037								1,617	
AUSTRALIA	16	7	14	1	1	1				40	1,309,679	1,357,747	127,694	16,161	1,749	47,393				2,860,423	1441.95
AUSTRIA	184	43	29	21	11	1				289	283,139	239,865	344,623	58,462	35,246	3,782				965,117	437.58
AZERBAIJAN	21	5	1		1					28	10,969	14,605	1,623		367					27,564	75.25
BAHAMAS	23	1	3	3						30	31,715	160	3,656	4,655						40,186	8.51
BAHRAIN	4	5		2	1					12	14,232	104,028		729	1,248					120,237	33.84
BANGLADESH	24	13		3						40	59,439	25,723		3,566						88,728	183.82
BARBADOS	2	1	1	2						6	3,020	257	200	1,713						5,190	4.35
BELARUS	17	2	7							26	10,101	15,299	10,705							36,105	76.14
BELGIUM	19	9	5	4	5					42	652,514	329,070	273,204	3,069	15,149					1,273,006	532.39
BELIZE	4	1			1					6	621	386			358					1,365	1.70
BENIN	8	1								9	2,765	1,431								4,196	9.59
BERMUDA	2		2							4	21,317		1,775							23,092	
BHUTAN	3									3	1,202									1,202	1.99
BOLIVIA	1	8	1	2						12	53	12,050	3,128	1,382						16,613	33.24
BOSNIA AND HERZEGOVINA	4	11	4	2	5					26	1,831	6,158	3,118	1,225	1,656					13,988	18.52
BOTSWANA	8	1	2							11	5,830	418	1,168							7,416	15.88
BRAZIL	83	36	17	5						141	1,376,576	599,875	29,506	74,468						2,080,425	2417.16
BRUNEI DARUSSALAM		1								1		2,706								2,706	17.10
BULGARIA	10	10	2	1						23	22,808	21,205	1,468	2,729						48,210	56.72
BURKINA FASO	5	3	1							9	1,158	3,029	611							4,798	12.48
BURUNDI	4	1		1						6	259	224		187						670	2.90
CAMBODIA	5	11	4	1	1	1				23	4,297	7,969	873	99	332	353				13,923	16.78
CAMEROON	5	1	3	3						12	959	433	2,957	2,936						7,285	31.63
CANADA	53	18	10	3	1					85	2,846,839	1,051,419	39,746	3,701	10					3,941,715	1783.78
CAPE VERDE	1	3	2							6	259	998	788							2,045	1.87
CAYMAN ISLANDS	19		1							20	22,196		12,376							34,572	
CENTRAL AFRICAN REPUBLIC	2									2	258									258	1.73
CHAD	4	1								5	814	319								1,133	13.94
CHILE	11	6	10	6	2					35	73,641	192,501	54,875	5,914	20,391					347,322	258.68
CHINA	111	34	13	29	3					190	20,605,051	725,637	217,344	1,504,762	25,481					23,078,275	10430.71
COLOMBIA	10	10	4	3						27	123,640	94,505	15,177	551						233,873	377.87
COMOROS	1									1	0									0	0.70
CONGO	5									5	3,147									3,147	13.55
COSTA RICA	25	13	5	3						46	17,819	28,841	1,065	213						47,938	49.60
COTE D'IVOIRE	7	3	6	1						17	1,640	2,658	5,176	376						9,850	33.74
CROATIA	8	10	11	3	1					33	5,984	46,496	15,954	749	366					69,549	57.17
CUBA	5	1								6	10,490	5,073								15,563	

	Number of Banks										Total Asset(millions of US dollar)										Nominal GDP (billions of US dollar)
	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	
CURACAO	13	1		2						16	11,647	3,703		1,463						16,813	
CYPRUS	11	6	3	1						21	60,348	62,969	53,753	529						177,599	23.11
CZECH REPUBLIC	9	8	2	1						20	93,674	107,793	3,958	271						205,696	205.27
DEMOCRATIC PEOPLE'S REPUB	1									1	8,955									8,955	
DEMOCRATIC REPUBLIC OF CO	5	8	1							14	913	3,109	131							4,153	35.92
DENMARK	34	25	10	8						77	55,066	99,672	134,603	716,900						1,006,241	346.12
DJIBOUTI	4	1								5	972	410								1,382	1.59
DOMINICA			1							1			375							375	0.52
DOMINICAN REPUBLIC	28	17	14	2						61	10,873	16,973	5,942	119						33,907	64.06
ECUADOR	6	9	4	2						21	6,285	24,036	5,940	1,936						38,197	100.92
EGYPT	16	4	1	2						23	155,170	11,839	1,634	47,083						215,726	301.39
EL SALVADOR	2	5	3	2	2					14	836	9,680	2,651	2,702	2,585					18,454	25.16
EQUATORIAL GUINEA	3									3	1,763									1,763	15.53
ERITREA	2									2	1,854									1,854	4.05
ESTONIA	5	1	1	1						8	22,246	233	311	311						23,101	26.51
ETHIOPIA	1	7	1	1						10	207	4,923	12,424	399						17,953	55.51
FEDERATED STATES OF MICRO	1									1	129									129	0.32
FIJI	1									1	405									405	4.53
FINLAND	38	3	2	2						45	574,425	152,017	349	65,636						792,427	272.77
FRANCE	128	51	28	18	2	3				230	6,953,615	4,961,192	3,770,293	51,662	785	1,484				15,739,031	2833.69
GABON	1	2	2	1	1					7	131	1,489	5,965	270	1,928					9,783	18.21
GAMBIA	7	1								8	346	104								450	0.82
GEORGIA	14	1								15	10,845	270								11,115	16.52
GERMANY	1,280	239	66	31	12					1,628	8,755,293	1,235,557	3,092,779	309,316	65,984					13,458,929	3874.44
GHANA	14	6	2	2						24	5,258	3,647	1,117	1,322						11,344	38.62
GIBRALTAR	2									2	5,474									5,474	
GREECE	4	5								9	10,781	433,608								444,389	235.95
GRENADA	1			1	1					3	204			278	313					795	0.91
GUATEMALA	8	2		10	3	1				24	11,344	799		22,113	3,469	173				37,898	58.83
GUINEA	6	1								7	653	410								1,063	6.70
GUINEA BISSAU	1									1	114									114	1.11
GUYANA		2	1							3		1,152	270							1,422	3.08
HAITI	4	1								5	3,655	109								3,764	8.71
HONDURAS	7	3	6	1		1	1			19	7,548	2,522	5,150	1,526		372	306			17,424	19.51
HONG KONG	27	5	3							35	1,895,556	158,181	3,129							2,056,866	291.23
HUNGARY	8	5	4	5	4	1				27	3,295	73,216	9,724	20,421	2,624	695				109,975	138.35
ICELAND	14	2	1							17	159,422	249	8,070							167,741	17.16
INDIA	54	15	8	3		1				81	1,615,932	355,212	19,492	6,558		3,413				2,000,607	2042.56
INDONESIA	60	18	3			1				82	374,962	59,895	2,662			329				437,848	890.60
IRAQ	6	1	4	1	1					13	4,219	412	3,114	268	479					8,492	223.51
IRELAND	10	3	1			1				15	225,999	209,285	15,146			16,649				467,079	250.81
ISLAMIC REPUBLIC OF IRAN	1									1	7,332									7,332	416.49
ISRAEL	10	2								12	364,103	6,268								370,371	305.67
ITALY	399	93	21	9	1		1		1	525	2,007,276	1,315,729	354,360	346,926	269		274		1,265	4,026,099	2141.94
JAMAICA	6	1								7	9,088	256								9,344	13.89
JAPAN	555	33	5							593	15,230,263	193,546	25,979							15,449,788	4596.16
JORDAN	8	2		1						11	29,743	50,691		36,421						116,855	35.88
KAZAKHSTAN	18	9	6	1						34	44,640	46,100	17,985	372						109,097	217.87
KENYA	32	3		1						36	37,487	365		289						38,141	60.94

	Number of Banks										Total Asset(millions of US dollar)										Nominal GDP
	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	(billions of US dollar)
KIRIBATI	1	1								2	27	122								149	0.19
KOSOVO	3	2								5	1,517	773								2,290	7.40
KUWAIT	3	1	1		1					6	104,380	14,363	17,917		13,303					149,963	171.96
KYRGYZSTAN	5		2	2	1					10	432		483	330	223					1,468	7.47
LAO PEOPLE'S DEMOCRATIC RE	5	2	2							9	4,233	496	304							5,033	11.69
LATVIA	7	9	2	1		1				20	9,643	23,203	781	304		278				34,209	31.34
LEBANON	34	8		5	1					48	117,629	72,592		37,338	206					227,765	49.94
LESOTHO	2	1		1						4	148	311		604						1,063	2.22
LIBERIA	3		1							4	73		279							352	2.01
LIBYA	6	4								10	56,416	7,620								64,036	44.42
LIECHTENSTEIN		1	1							2		669	361							1,030	
LITHUANIA	4	3	1	2						10	24,641	2,587	2,146	300						29,674	48.47
LUXEMBOURG	25	23	15	6	2					71	209,156	363,201	82,838	3,923	3,959					663,077	64.98
MACAO	6	2	1	1						10	25,935	31,416	112	150						57,613	55.52
MACEDONIA (FYROM)	8	5	2		1					16	3,641	2,533	927		318					7,419	11.33
MADAGASCAR	3		2	1						6	950		628	401						1,979	10.67
MALAWI	4	1	2		1					8	1,018	222	137		103					1,480	6.06
MALAYSIA	20	14	2							36	526,240	174,995	789							702,024	338.11
MALDIVES	1									1	1,179									1,179	3.06
MALI	6	3		1						10	916	2,374		644						3,934	14.45
MALTA	9	3	1							13	24,699	2,021	536							27,256	10.74
MAURITANIA	6	2	1	1						10	1,127	236	163	140						1,666	5.30
MAURITIUS	5	6	1	5						17	15,305	10,605	3,231	8,132						37,273	12.63
MEXICO	24	18	11	8	3	1				65	145,916	252,836	34,409	36,873	391	359				470,784	1297.85
MONGOLIA	7	1		1						9	1,648	2,150		781						4,579	12.20
MONTENEGRO	3	1	2	2		1				9	1,231	706	472	630		285				3,324	4.60
MOROCCO	8	3	4		1					16	84,532	95,839	23,250		3,049					206,670	110.01
MOZAMBIQUE	8	3	1	1						13	8,633	824	319	375						10,151	16.86
MYANMAR	11	1		1						13	551,525	179		5,522						557,226	65.75
NAMIBIA	3	2		1						6	3,523	4,881		1,883						10,287	13.19
NEPAL	8	7	4	7	3	1				30	3,599	3,834	2,311	4,889	1,069	477				16,179	19.76
NETHERLANDS	14	15	4	1						34	1,879,558	1,122,609	51,090	766						3,054,023	880.72
NEW ZEALAND	3	9	7	3	2					24	1,527	264,776	74,001	2,868	159					343,331	197.93
NICARAGUA	6									6	5,813									5,813	11.81
NIGER	5	1		1						7	691	431		429						1,551	8.26
NIGERIA	12	6	1	1						20	127,573	23,153	675	1,483						152,884	574.00
NORWAY	70	31	19	9	1					130	404,326	95,215	35,785	61,185	193					596,704	500.52
OMAN	2	2	2							6	37,348	11,462	17,832							66,642	77.77
PAKISTAN	18	3				1				22	110,300	3,922				9				114,231	243.38
PALESTINIAN TERRITORIES	1	1			1					3	2,425	669			279					3,373	0.25
PANAMA	52	11	11	4						78	41,083	48,724	11,305	3,995						105,107	49.17
PAPUA NEW GUINEA	4									4	10,752									10,752	16.65
PARAGUAY	3	5	5	5						18	3,696	7,057	3,807	4,037						18,597	30.88
PERU	6	4	1	9						20	18,411	66,660	690	22,673						108,434	202.90
PHILIPPINES	33	11	10	3						57	128,842	45,889	50,488	19,347						244,566	284.78
POLAND	21	12	4	3	5	2				47	169,073	172,667	28,596	4,302	7,693	5,467				387,798	544.86
PORTUGAL	62	36	12	3	2					115	147,780	301,485	15,495	191,662	79,598					736,020	230.48
QATAR	5	2								7	60,552	181,884								242,436	210.11
REPUBLIC OF KOREA	8	6	4	1	5					24	402,300	382,133	532,250	1,031	22,478					1,340,192	1410.38
REPUBLIC OF MOLDOVA	7	3	1	2						13	2,648	311	26	875						3,860	7.98

	Number of Banks										Total Asset(millions of US dollar)										Nominal GDP
	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	0%-10%	10%-20%	20%-30%	30%-40%	40%-50%	50%-60%	60%-70%	70%-80%	80%-90%	Country Total	(billions of US dollar)
ROMANIA	6	9	7	3	2	1				28	14,088	33,901	26,593	13,572	4,948	334				93,436	199.37
RUSSIAN FEDERATION	132	45	344	283	24	3				831	1,029,291	177,322	124,970	58,073	10,672	238				1,400,566	2029.62
RWANDA	5	1		2						8	1,257	285		409						1,951	7.89
SAINT KITTS AND NEVIS	1	1								2	195	1,356								1,551	0.85
SAINT LUCIA	4	1								5	1,323	1,379								2,702	1.40
SAINT VINCENT AND THE GRENA	1									1	301									301	0.73
SAMOA	3									3	309									309	0.82
SAN MARINO	2	3								5	309	4,542								4,851	1.85
SAO TOME AND PRINCIPE	3									3	37									37	0.34
SAUDI ARABIA	8									8	432,362									432,362	753.83
SENEGAL	3	2	5	1	1					12	820	778	3,461	699	1,365					7,123	15.36
SERBIA	12	7	6	3	2	1				31	10,296	5,159	11,822	1,549	1,883	319				31,028	44.21
SEYCHELLES	4	2								6	646	580								1,226	1.35
SIERRA LEONE	10	1								11	709	71								780	4.75
SINGAPORE	17	3	1							21	928,556	30,223	310							959,089	306.36
SINT MAARTEN	1									1	623									623	
SLOVAKIA	9	3	2							14	45,180	19,143	4,102							68,425	100.33
SLOVENIA	6	10	1		2					19	6,542	36,068	1,300		860					44,770	49.57
SOUTH AFRICA	10	4	1		1					16	315,712	649	3,651		27					320,039	350.14
SOUTH SUDAN	5									5	568									568	13.90
SPAIN	80	32	19	6	4			1		142	1,970,542	1,219,637	1,939,048	12,757	12,150			13,194		5,167,328	1383.54
SRI LANKA	10	4		4						18	39,683	10,147		1,533						51,363	75.05
SUDAN	8		1							9	2,808		182							2,990	74.36
SURINAME	1			1	2					4	90			1,237	805					2,132	5.21
SWAZILAND	1	3								4	310	840								1,150	4.42
SWEDEN	74	7	1	3						85	661,030	304,789	563	5,211						971,593	571.10
SWITZERLAND	237	67	11	11		1				327	1,584,496	1,135,554	56,579	10,637		271				2,787,537	701.23
SYRIAN ARAB REPUBLIC	10	3								13	27,997	1,780								29,777	
TAIWAN	39	4	1	1		1				46	1,451,115	227,072	25,829	4,330		382				1,708,728	530.04
TAJIKISTAN	5	1			1					7	1,395	60			340					1,795	9.24
THAILAND	5	6	9	2	1					23	32,781	265,736	284,832	7,877	8,435					599,661	404.32
TOGO	3	2		1						6	509	1,436		194						2,139	4.61
TONGA	1									1	109									109	0.43
TRINIDAD AND TOBAGO	7	1	2							10	21,232	3,900	6,166							31,298	27.27
TUNISIA	6	6	3		2					17	6,111	13,238	11,328		5,922					36,599	47.61
TURKEY	23	6	4	2						35	630,271	167,915	6,137	146						804,469	798.33
TURKMENISTAN	1			1						2	5,002			2,167						7,169	46.22
TUVALU	1									1	20									20	0.04
UGANDA	16	1	2							19	5,463	266	194							5,923	27.52
UKRAINE	19	65	58	6	3					151	15,676	28,102	38,077	1,086	65					83,006	132.34
UNITED ARAB EMIRATES	8	7	4							19	215,505	183,895	73,201							472,601	399.45
UNITED KINGDOM	63	34	25	18	6					146	6,330,619	353,267	2,458,011	1,174,218	1,734					10,317,849	2991.69
UNITED REPUBLIC OF TANZANIA	25	2	3	2	1					33	13,290	504	733	255	69					14,851	48.09
UNITED STATES OF AMERICA	5,857	778	208	76	24	6	2	1	1	6,953	12,991,678	1,654,967	267,778	1,374,887	83,455	1,808	8,177	690	113	16,383,553	17348.08
URUGUAY	13	10	4							27	24,220	11,196	3,709							39,125	57.47
UZBEKISTAN	9	4	3	2	1					19	4,568	3,898	4,236	493	5,248					18,443	63.10
VANUATU	1	1								2	252	141								393	0.82
VENEZUELA	15	1	20	2						38	37,641	2,310	523,950	90,935						654,836	250.28
VIETNAM	16	21	4	3	3	1				48	66,397	151,559	4,899	5,606	5,326	123				233,910	185.90
YEMEN	5	1								6	3,441	2,227								5,668	43.23
ZAMBIA	9	5	1	1						16	4,183	2,050	360	289						6,882	27.14
ZIMBABWE	9	1	3		1					14	2,733	159	1,019		287					4,198	14.20

Appendix B

List of variables used to build the random forests EWS.

List of incorporated bank-level variables

- Interest Income on Loans/Average Gross Loans
- Interest Expense on Customer Deposits/Average Customer Deposits
- Interest Income/Average Earning Assets
- Interest Expense/Average Interest-bearing Liabilities
- Net Interest Income/Average Earning Assets
- Net Int. Increase Less Loan Impairment Charges/Average Earning Assets
- Net Interest Increase Less Preferred Stock Dividend/Average Earning Assets
- Non-Interest Income/Gross Revenues
- Non-Interest Expense/Gross Revenues
- Non-Interest Expense/Average Assets
- Pre-impairment Operating Profit/Average Equity
- Pre-impairment Operating Profit/Average Total Assets
- Loans and securities impairment charges/Pre-impairment Operating Profit
- Operating Profit/Average Equity
- Operating Profit/Average Total Assets
- Taxes/Pre-tax Profit
- Pre-Impairment Operating Profit/Risk Weighted Assets
- Operating Profit/Risk Weighted Assets
- Net Income/Average Total Equity
- Net Income/Average Total Assets
- Fitch Comprehensive Income/Average Total Equity
- Fitch Comprehensive Income/Average Total Assets
- Net Income/Risk Weighted Assets
- Fitch Comprehensive Income/Risk Weighted Assets
- Tangible Common Equity/Tangible Assets
- Tier 1 Regulatory Capital Ratio
- Total Regulatory Capital Ratio
- Equity/Total Assets
- Cash Dividends Paid and Declared/Net Income
- Cash Dividend Paid and Declared/Fitch Comprehensive Income
- Net Income–Cash Dividends/Total Equity
- Growth of Total Assets
- Growth of Gross Loans
- Impaired Loans (NPLs)/Gross Loans
- Reserves for Impaired Loans/Gross loans
- Reserves for Impaired Loans/Impaired Loans
- Impaired Loans less Reserves for Impaired Loans/Equity
- Loan Impairment Charges/Average Gross Loans
- Net Charge-offs/Average Gross Loans
- Impaired Loans + Foreclosed Assets/Gross Loans + Foreclosed Assets
- Loans/Customer Deposits
- Customer Deposits/Total Funding excluding Derivatives

List of eliminated bank-level variables (variables with missing values more than 50% of observations)

- Net Income/Average Total Assets + Average Managed Securitized Assets
- Fitch Core Capital/Weighted Risks
- Fitch Eligible Capital/Weighted Risks
- Core Tier 1 Regulatory Capital Ratio
- Cash Dividends and Share Repurchase/Net Income
- Interbank Assets/Interbank Liabilities

Appendix C

Evaluating classification accuracy

To evaluate the classification accuracy of the random forests EWS, we used K-fold cross-validation, which is a standard resampling technique used for estimating model performance. The basic idea involves using parts of the sample data to fit the model (training set) and the remaining part to estimate the prediction error of the model (validation set). First, we randomly split the observations into K folds of roughly equal size. Then, we treated one of the K folds as a validation set and fit the model on the remaining K–1 folds. We calculated the prediction error of the observations in the validation set. We repeated the process K times to obtain K different estimates of the prediction error. The K-fold cross-validation estimate of the prediction error is the average of these values. Since the typical choice of K is either 5 or 10, we used a 10-fold cross-validation. Using the same setup, we compared the performance of the random forests EWS with that of conventional EWSs based on a logistic regression and a decision tree. The random forests model produced an accuracy rate of 93.64%, whereas the logistic regression and decision tree produced accuracy rates of 65.73% and 73.75%, respectively. The result clearly indicates that random forests can build more reliable EWSs than conventional methods.

We also conducted a historical back test to evaluate the classification accuracy. More specifically, we predicted the bank status (active or inactive) in 2013 and 2014 based on banks' financial statements in 2013, excluding those that became inactive before 2013. We evaluated performance in terms of accuracy by comparing the predicted bank status with the actual status in 2013 and 2014. The random forests model produced an accuracy rate of 85.27%, whereas the logistic regression and decision tree produce accuracy rates of 53.44% and 56.43%, respectively. Once again, the result clearly indicates that the random forest EWS outperforms the conventional EWSs.

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