Core Matters

Let the data speak: a new approach to sovereign risk assessment

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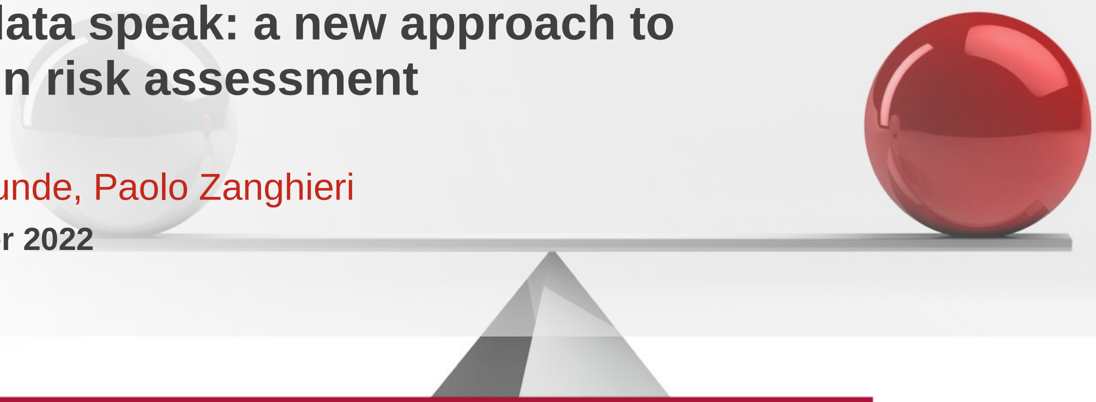
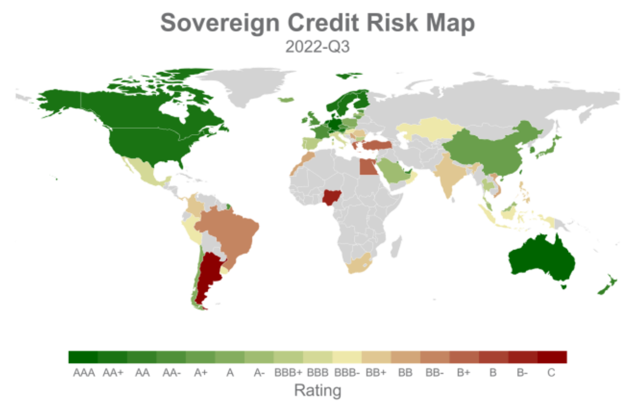


Our Core Matters series provides thematic research on macro, investment, and insurance topics

- Insurance companies and asset managers need to rely on proprietary internal rating for sovereign bonds in order not to be exclusively dependent on rating agencies.
- We introduce a new internal rating model that provides a purely quantitative assessment of sovereign credit risk, without resorting to potentially opaque subjective adjustments made by rating agencies. It uses a framework based on empirical evidence on the determinants of sovereign stress. The model relies on a limited set of parameters which are empirically validated and supported by economic theory. It can easily be applied to a large set of countries.
- As no manual, qualitative adjustments are made, our model results – opposite to those of the rating agencies – cannot be criticised for subjective bias.



Source: GIAM calculations

- The model uses available macro data (including medium-term projections) in an efficient and transparent way, blending two approaches: a) a panel regression model, to perform out-of-sample projections, and b) a machine learning algorithm (k-means) to cluster countries according to credit risk indicators.
- We currently cover 72 countries, with a focus on those most relevant for a liability-driven manager like Generali Insurance Asset Management (GIAM). The structure of the model is flexible enough to allow for a quick extension of the country coverage. In total, the model is based on a manageable set of roughly 20 economic time series variables.

CONTENT

1. Introduction

When dealing with credit risk both at the corporate and sovereign level, there is hardly any way around the major Credit Rating Agencies (CRAs), including e.g., Moody's, S&P, and Fitch. Their ratings are widely used and generally accepted. However, at least since the Enron crisis, the agencies have repeatedly come under criticism, not least for the lack of transparency in their approaches. All agencies apply subjective and sometimes sizeable adjustments to their model-derived ratings, decided by a committee roughly every six months, following rules and methodologies that are not disclosed.

Thus, the regulator asks insurance companies and asset managers to perform their own independent assessment of credit risk. In this report we present our new tool. It provides a fully data-driven and transparent approach, with no subjective interventions at all. Our sovereign ratings are built from publicly available data, and use both historical data and projections, sourced from the IMF and the World Bank. However, we still use the information contained in the agencies' ratings, for two reasons: firstly, CRAs devote a lot of resources to analysing sovereigns, incl. on political and other less quantitative risks, and therefore their output provides a lot of information. Secondly, and more prosaically, clients will never stop looking at the blends of CRAs' ratings. Therefore, CRA ratings, will always be seen as a sort of benchmark. A useful proprietary assessment should in the first place provide early signals when CRA ratings deviate more visibly from a fully transparent quantitative assessment.

The following sections present GIAM's internal approach to modelling sovereign credit risk. We shed some light on the construction details, without going into the full technical details. We will present the input data as well as how and where they enter the approach and for what purpose. Finally, we show some examples of how the results are summarised and presented graphically.

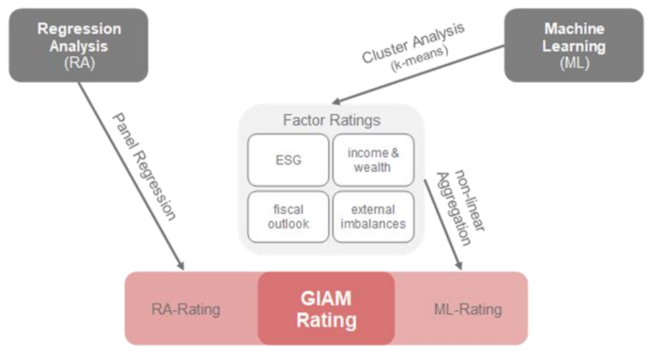
Compared with the sovereign rating methodologies used by agencies or central banks our approach innovates in two ways. Firstly, it employs machine learning (ML) to group countries according to macroeconomic and fiscal metrics without resorting to arbitrary thresholds. Secondly, instead of limiting ourselves to the proxies for the quality of governance and rule of law commonly used in sovereign credit risk analysis, we include an ESG index (MSCI) to include a broader assessment that makes a step towards integrating environmental and social concerns into sovereign rating.

2. The Model – A two-pillar Approach

The rating generated by the model is based on two equally weighted sub-ratings (see chart below).

The first pillar is a "classical" regression analysis that aims at out-of-sample predictions of the average CRA[1] rating country by country. The second pillar resorts to machine learning (ML). We apply cluster analysis to derive factor ratings, for each country, which are then aggregated to a single rating.

The Model's Two Pillars



Source: GIAM

CRAs ratings slightly differ in scale and definitions (see Appendix B). The rating scale we apply mostly coincides with those used by S&P and Fitch. Below B- we do not differentiate and just keep a single rating class C. All in all, we cover 17 rating classes from AAA to C. For any kind of calculation and model estimation, the alphanumerical ratings are mapped linearly into numerical scores. The two terms rating and score

[1] If not stated differently, CRA exclusively refers to Moody's, S&P, and Fitch.

are used synonymously in the following. The differentiation is revealed from the context.

In line with the academic/policy-oriented literature on sovereign risk and with the CRAs practice we identify five areas of vulnerability, which guide the selection of the variables:

(1) **ESG/Governance:** The theory behind the standard rating model states that the quality of government influences fiscal policies and the sustainability of debt. We take a broader approach and use MSCI indices that assess countries not just in terms of governance but also social inclusion and environmental risk and policies.

(2) **Wealth & size:** Richer countries have a potentially wider tax base, making debt easier to sustain. Moreover, bigger countries may enjoy a "too big to fail" premium, as their sovereign debt is more liquid and a fiscal crisis there could have a systemic impact.

(3) **Economic performance:** Sustained growth eases the debt burden in the medium term, while a large slump in activity or employment makes it more difficult for a country to keep a prudent fiscal stance. At the same time elevated inflation, while easing the debt burden is more often a sign of poor economic governance, adding to sustainability concerns.

(4) **Fiscal performance:** Debt dynamics is the key metric; however, we try to distinguish between the genuine fiscal stance, proxied by the primary balance, and the share of expenditures largely beyond the control of the Treasury, proxied by the ratio of interest expenditure to fiscal revenue. We also consider the health of the banking system, to assess the risk deriving from the need to bail out banks to stem the risk of a crisis.

(5) **FX and external imbalances:** countries issuing a liquid and widely used currency which plays a big role in central banks' reserves benefit in terms of debt sustainability as they have a limited incentive to issue debt in foreign currency. We use this information in conjunction with other, more standard metrics such as import coverage (FX reserves to import) or external debt.

The choice of the individual indicators for the regression model derives from formal statistical testing. In the machine learning one, we draw from the determinants of sovereign ratings identified by empirical literature and from the variables chosen by rating agencies .

2.1 The Regression Model

Although CRAs take different approaches – blending a fully disclosed quantitative model with a rather opaque subjective adjustment – they tend to broadly agree in the assessment of individual countries' credit risk[2]. It can therefore be assumed that ratings are largely determined by a set of common factors whose significance for credit risk is generally undisputed. This motivates the use of a regression model. By identifying a sensible set of fundamentals, it predicts the average CRA rating of a country. By taking a long-term view, these predictions should generally correspond to the objective parts of the CRAs' approaches.

The average CRA rating of a country is regressed on these independent (quarterly) variables, using an expanding sample beginning in 2012, to account for the effect of the Great Financial crisis on CRAs methodologies. Afterwards, the coefficients are used for out-of-sample projections: the four quarterly ratings for year *t* are computed with the coefficients estimated up to *t-1*. This allows us to filter out the subjective component of each CRA. We use a Tobit specification (see box on p. 4) to account for the fact that the dependent variable is bounded between 1 (AAA) and 17 (C).

Regression model estimates

Dependent Variable: Average of the three main CRA rating (A to "below B-"). Tobit estimation

Variable	Coef.	Std. Err.	z-Stat.	Prob.
Constant	-2.940	1.418	-2.074	0.038
ESG × EM dummy	0.313	0.068	4.613	0.000
ESG × AE dummy	1.528	0.105	14.598	0.000
Share in world GDP	16.082	3.256	4.939	0.000
Per capita PPP GDP (log)	0.994	0.167	5.960	0.000
Unemployment rate	-0.153	0.009	-17.395	0.000
GDP growth (5yr avg. Centered on curr. Year)	0.065	0.014	4.514	0.000
Gov't debt to GDP (country median)	-0.066	0.004	-16.770	0.000
Gov't debt to GDP (deviaton from median)	-0.046	0.002	-22.409	0.000
Intrest exp. to revenue	-0.104	0.010	-10.700	0.000
Reserves on import × Non reserve currency dummy	0.265	0.039	6.827	0.000
Reserve currency dummy	0.796	0.171	4.660	0.000

We use the regression to test different hypotheses on what drives the rating. We chose the final specification based on the statistical significance of the coefficients, the consistence with loose theoretical priors, aiming at taking all the dimensions of sovereign rating. The econometric analysis uncovered some interesting facts:

- **ESG considerations matter** for sovereign rating: this is not very surprising given the significant correlation between the MSCI scores and the World Bank governance measures. What is interesting is the differing impact on EMs and AMs ratings, as the coefficient of the latter is nearly five times larger. This may indicate that ESG factors become important to discriminate among countries only when they are above a certain level of economic development.

[2] The correlation between the ratings of different Agencies is usually well above 0.95.

- **The economic weight** (proxied by the country's share in world GDP) is important, confirming the "too big to fail" hypothesis".
- **Global and national debt cycles** are important: the median level of debt to GDP across the sample is statistically significant, as well as its country-specific evolution. Debt servicing costs are also very relevant.

The Tobit regression

The specification is composed of:

- a linear, latent variable model

$$Y_t^* = \alpha + \sum_{i=1}^{N} \beta_i X_{it} + \sigma\epsilon_t$$

- and a set of identities linking it to the actual variable

$$Y_t = \begin{cases} C_{LOW} & \text{for} \quad Y_t^* \leq C_{LOW} \\ Y_t^* & \text{for} \quad C_{LOW} < Y_t^* < C_{HIGH} \\ C_{HIGH} & \text{for} \quad Y_t^* \geq C_{HIGH} \end{cases}$$

The parameters are estimated by maximizing the function

$$\begin{aligned} l(\alpha,\beta_i,\sigma) \quad = \quad & \sum_{t=1}^{T} \log\left[\frac{f\left(Y_t - \alpha - \sum_{i=1}^{N}\beta_i X_{it}\right)}{\sigma}\right] \\ \times \quad & (1 \text{ if } C_{LOW} < Y_t < C_{HIGH},\ 0 \text{ otherwise}\ ) \\ + \quad & \sum_{t=1}^{T} \log\left[\frac{F\left(C_{LOW} - \alpha - \sum_{i=1}^{N}\beta_i X_{it}\right)}{\sigma}\right] \\ \times \quad & (1 \text{ if } Y_t = C_{LOW},\ 0 \text{ otherwise}\ ) \\ + \quad & \sum_{t=1}^{T} \log\left[\frac{1 - F\left(C_{HIGH} - \alpha - \sum_{i=1}^{N}\beta_i X_{it}\right)}{\sigma}\right] \\ \times \quad & (1 \text{ if } Y_t = C_{HIGH},\ 0 \text{ otherwise}\ ) \end{aligned}$$

Where f and F are respectively the density and cumulative distribution function of the error term ϵ, assumed to be logistic.

In our case $C_{LOW} = 1$, $C_{HIGH} = 17$

- **Having a reserve currency** or one that is widely used in international trade is important, as it may mitigate the liquidity squeezed associated with the risk of balance of payment crises.
- **The import cover ratio** (FX reserves divided by import) is significant only for countries that do not issue a reserve currency, for which FX volatility is arguably higher and more dangerous for economic and debt sustainability.

2.2 The Machine Learning Pillar

The machine learning pillar classifies countries by their credit risk along four economic dimensions. As there is no "true" observable classification this is a typical usecase for a so-called unsupervised classification like cluster analysis. We perform this analysis by applying the k-means algorithm (see box on p. 5).

For each of the four dimensions countries are clustered according to one or two core variables in a first step. In a second step, each partial rating is adjusted by up to ±2 notches considering a richer set of variables (see graph on p. 6 for the basic mode of operation and Appendix C for technical details). Then the final rating is obtained as an average[3] of the partial ratings. The methodology echoes those of S&P and Moody's. A key difference is that the initial ratings are not based on exogenous thresholds but are fully determined by the data. Moreover, the four sub-ratings used in the ML approach are averaged without recourse to ad hoc weighting schemes, increasing transparency.

2.2.1 The Credit Risk Dimensions

The four dimension we consider are:

(1) **ESG**: The quality of public governance has long been a key factor in credit risk assessment, we complement it with the consideration of the environmental and social performances.

(2) **Income and wealth**: The income level is a proxy for the possibility of the state to raise revenues and address a fiscal shortfall.

(3) **Fiscal outlook**: The size of the debt as a share of GDP and its resilience to interest rate shocks are crucial determinants of actual and perceived debt sustainability. On top of that, we consider measures of the fiscal policy stance and the role of implicit liabilities related to the banking sector.

(4) **External imbalances**: current account/external debt crisis may turn into an exchange rate crisis and ultimately affect a government's solvency.

The choice of the variables used to represent these dimensions for clustering the countries is based on two considerations. We take the variable we deem the most economically relevant, and tend to prefer those moving relatively slowly, to ensure sufficient stability in the core rating.

For **ESG** we use – consistent with the Generali Group guidelines – the MSCI country ESG score. The model can of course accommodate other choices.

[3] The four adjusted scores are averaged to get the final rating ML_{it} for county *i* in quarter *t*. To account for potential nonlinearities in the number to letter conversion the average is computed on the logit of the final rating. This aggregation implies that the final rating from the ML algorithm does not need to correspond with the simple average of the partial ratings.

$$ML_{it} = \frac{e^{\left(\text{Score}_{it}^{ESG} + \text{Score}_{it}^{WEALTH} + \text{Score}_{it}^{FISCAL} + \text{Score}_{it}^{EXT}\ /_4\right)}}{1 + e^{\left(\text{Score}_{it}^{ESG} + \text{Score}_{it}^{WEALTH} + \text{Score}_{it}^{FISCAL} + \text{Score}_{it}^{EXT}\ /_4\right)}}$$

For **income and wealth**, we initially cluster countries according to their per capita GDP. It is an intuitive and widely used measure of a country's level of development. To derive the final rating, we perform two adjustments. We first consider the distance between the average GDP growth and the median growth differentiated by EMs and AMs. The average GDP growth is computed on a five-year period centered around the current year, using the most recent IMF forecasts. This approach looks through cyclical variations and introduces a forward-looking component. The second adjustment penalizes countries with elevated growth volatility (10-year standard deviation), as this can harm fiscal sustainability.

For the **fiscal outlook** we first cluster countries using the debt to GDP ratio and the interest expenditure to revenues ratio. We use two partial ratings to stress the importance of the debt sustainability and its resilience to interest rate shocks. We adjust the interest expenditure to revenues ratio by considering the fiscal policy stance, measured by a three-year average of the primary balance to GDP ratio and the volatility of government revenues (10-year standard deviation). Moreover, to adjust the debt to GDP ratio, we consider the implicit debt burden related to the risk of having to bail out the banking sector. For this we use the share of non-performing loans to bank capitalization, multiplied by the size of the banking sector in the economy.

k-means

k-means aims at classifying data into k clusters S_i such that the squared sum J of the differences from the cluster-centroids μ_i is minimized:

$$J = \sum_{i=1}^{k} \sum_{x_j \in S_i} \|x_j - \mu_i\|^2$$

The centroids μ_i are just the averages of the classification variable(s) calculated across the cluster members $x_j \in S_i$. In case of n classification variables μ_i and x_j are vectors of dimension *(nX1)*. The solution of the equation is derived iteratively through two steps per iteration:

1. Calculate the k centroids μ_i. *(In the first iteration this can for example be done by randomly choosing k datapoints.)*
2. Assign each datapoint x to the cluster S_i with the nearest centroid μ_i until all datapoints are classified.

Repeat the two steps until the assignment of the datapoints does not change anymore between iterations.

As the result depends on the starting points, the whole procedure is repeatedly applied (500 times in our case) and the best one taken.

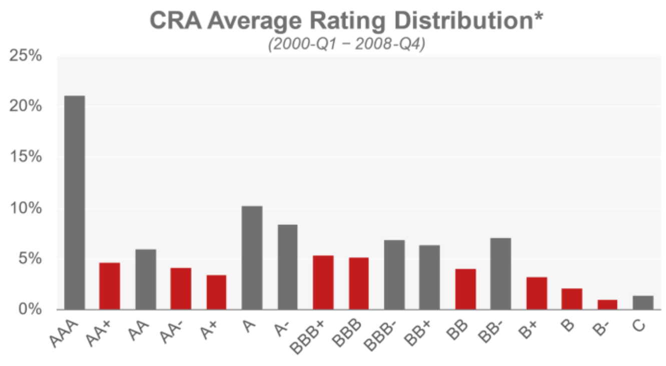
For the **external imbalances,** we cluster according to the ratio of the Net International Investment Position (a stock variable) and the average of the current account to GDP ratio (again calculated with a 5-year average centered on the current year, using IMF forecasts). We then average the two scores. Finally, we adjust this combined rating using the external debt to GDP ratio, to take into consideration the risks stemming from debt rollover and default, and the depth of the market for the domestic currency, to account for market liquidity risk[4].

Additionally, we apply adjustments to the external and fiscal scores based on the flexibility of the exchange rate regime and the size of the credit sector relative to the economy. The first gauges the extent to which the exchange rate can absorb economic fluctuations. The EMs experience from the 1998 Asian crisis onwards shows that tight FX regimes may stand in the way of a successful fiscal response to shocks. The size of the credit sector is an enabling factor for monetary policy transmission and, more importantly, a measure of the relative scope of the domestic market to absorb government debt.

Finally, in accordance with the empirical literature, a two and one notch(es) rating uplift is assigned to the TOP 5 and TOP 10 countries in terms of GDP level respectively("too-big-to-fail").

2.2.2 Technical Implementation

As stated in section 1.2 we implement the credit risk classification task with cluster analysis by applying the k-means algorithm. Classical approaches explicitly define limits for the various classes. This could be done by using quantiles, that could be directly derived from the data but would lead to a uniform rating distribution by construction. Unfortunately, there is strong empirical evidence that ratings are not uniformly distributed (see chart below). Another option would be to use explicit thresholds. They could theoretically be adjusted towards any desired target distribution but are quite arbitrary and time-consuming to maintain across different variables and time.



Source: Bloomberg, GIAM calculations
*Average rating across CRAs for the 72 countries covered.

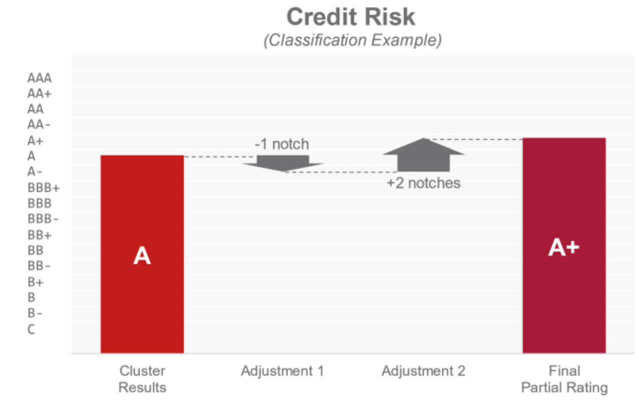
The k-means algorithm uses so-called centroids (see box on the left) instead of thresholds to classify the data. This

[4] The market for the domestic currency is considered liquid if the currency is actively traded or a reserve currency, based on recent research by the IMF. Having a reserve or actively traded currency leads to a rating upgrade by one notch.

approach is completely data driven. Once the number of clusters is fixed it can be run automatically. No maintenance and/or arbitrary interventions are necessary.

We are still left with two issues at this stage. First, the rating distribution does not match that of the CRAs data at all. Thus, we just cluster the countries based on the extreme and modal values of the historical rating distribution (see chart on p. 5, grey bars). Coverage of the remaining rating classes (see chart on p. 5, red bars) is achieved through the adjustments (see graph below for the basic mode of operation and Appendix C for technical details). Second, clustering produces a relative classification of credit risk. As the number of clusters is fixed there will always be countries assigned to any rating between AAA and C irrespective of the global economic conditions, i.e., there will be no empty clusters.

As investors seek absolute measures of risk, we apply the k-means algorithm not only to the current quarter Q_t but to the full (expanding) sample from Q_0 to Q_t, i.e., not only across countries but also across time. In doing so, we are still left with the issue of no empty clusters. But now, it applies to the totality of all combinations of countries and quarters and not necessarily to all countries in a particular quarter.



Source: GIAM

Thus, filtering out just the current quarter in a subsequent step allows for the existence of "empty" clusters with respect to individual quarters and that sense for a more absolute risk classification.

To ensure long-term coherence with the CRAs' rating distribution we apply a last, rather technical adjustment to the partial ratings. Country-wise, we calculate the long-term difference between the CRAs' average rating and the equally weighted average of our partial ratings. 50% of this difference is subtracted from the partial ratings. As our empirical backtesting suggests, this generally shifts the level of our ratings towards the CRAs' ratings but has no impact on the dynamics originated by the model.

At the end of the process, we get a raw score ranging from 1 to 17, which we round to get the AAA to C rating.

3. The Quarterly Analysis

The internal ratings are updated at the end of each quarter. As Appendix D shows, the results are presented alongside the range of the CRA ratings and the evolution of the sub-ratings and convey information about the drivers of changes in the internal assessment. We do not provide a measure of outlook, but rather indicate the medium-term (one year) trend.

4. Final Remarks

We developed a purely data-driven methodology for our internal sovereign ratings, aiming at a balance between the full independence from CRAs scores and the useful information they nevertheless convey. We use the information in two different ways, feeding a proprietary unsupervised machine learning algorithm and a regression model with out-of-sample forecasts. This modeling framework can have other applications: for example, to get an internal rating for corporate bonds, replacing macro variables with firms' fundamentals. The clustering algorithm could be fed for example with more granular environmental and social data to derive in a transparent way a country ESG score.

Country Coverage

Euro Area Core (12)	Euro Area Periphery (7)	CEEC (11)	Other Europe (6)
Austria	Cyprus	Bulgaria	Denmark
Belgium	Greece	Croatia	Iceland
Estonia	Ireland	Czechia	Norway
Finland	Italy	Hungary	Sweden
France	Malta	Kazakhstan	Switzerland
Germany	Portugal	Poland	United Kingdom
Latvia	Spain	Romania	
Lithuania		Russian Federation	
Luxembourg		Serbia	
Netherlands		Turkey	
Slovakia		Ukraine	
Slovenia			

Americas (10)	Asia (14)	Middle East / Africa (12)
Argentina	Australia	Bahrain
Brazil	China	Egypt
Canada	Hong Kong	Israel
Chile	India	Kuwait
Colombia	Indonesia	Morocco
Mexico	Japan	Nigeria
Panama	Korea, Republic of	Oman
Peru	Malaysia	Qatar
United States of America	New Zealand	Saudi Arabia
Uruguay	Philippines	South Africa
	Singapore	Tunisia
	Taiwan, Province of China	United Arab Emirates
	Thailand	
	Viet Nam	

Appendix B – Ratings Overview

Ratings – Scale- & Definition-Map*

S&P	Moody's	Fitch	S&P	Moody's	Fitch	S&P	Moody's	Fitch	GIAM
Investment Grade	Investment Grade	Investment Grade	Extremely strong capacity to meet financial commitments	Highest intrinsic, or standalone, financial strength, and thus subject to the lowest level of credit risk absent any possibility of extraordinary support from an affiliate or a government	owest expectation of default risk. They are assigned only in cases of exceptionally strong capacity for payment of financial commitments. This capacity is highly unlikely to be adversely affected by Lforeseeable events	AAA	Aaa	AAA	AAA
			Very strong capacity to meet financial commitments	High intrinsic, or standalone, financial strength, and thus subject to very low credit risk absent any possibility of extraordinary support from an affiliate or a government	Very low default risk. They indicate very strong capacity for payment of financial commitments. This capacity is not significantly vulnerable to foreseeable events	AA+	Aa1	AA+	AA+
						AA	Aa2	AA	AA
						AA-	Aa3	AA-	AA-
			Strong capacity to meet financial commitments, but somewhat susceptible to economic conditions and changes in circumstances	Upper-medium-grade intrinsic, or standalone, financial strength, and thus subject to low credit risk absent any possibility of extraordinary support from an affiliate or a government	Low default risk. The capacity for payment of financial commitments is considered strong. This capacity may, nevertheless, be more vulnerable to adverse business or economic conditions than is the case for higher ratings	A+	A1	A+	A+
						A	A2	A	A
						A-	A3	A-	A-
			Adequate capacity to meet financial commitments, but more subject to adverse economic conditions	Medium-grade intrinsic, or standalone, financial strength, and thus subject to moderate credit risk and, as such, may possess certain speculative credit elements absent any possibility of extraordinary support from an affiliate or a government	Expectations of default risk are currently low. The capacity for payment of financial commitments is considered adequate, but adverse business or economic conditions are more likely to impair this capacity	BBB+	Baa1	BBB+	BBB+
						BBB	Baa2	BBB	BBB
						BBB-	Baa3	BBB-	BBB-
Speculative Grade	Non-Investment Grade	Speculative Grade	Less vulnerable in the near-term but faces major ongoing uncertainties to adverse business, financial and economic conditions	Speculative intrinsic, or standalone, financial strength, and are subject to substantial credit risk absent any possibility of extraordinary support from an affiliate or a government	Elevated vulnerability to default risk, particularly in the event of adverse changes in business or economic conditions over time; however, business or financial flexibility exists that supports the servicing of financial commitments	BB+	Ba1	BB+	BB+
						BB	Ba2	BB	BB
						BB-	Ba3	BB-	BB-
			More vulnerable to adverse business, financial and economic conditions but currently has the capacity to meet financial commitments	Speculative intrinsic, or standalone, financial strength, and are subject to high credit risk absent any possibility of extraordinary support from an affiliate or a government	Material default risk is present, but a limited margin of safety remains. Financial commitments are currently being met; however, capacity for continued payment is vulnerable to deterioration in the business and economic environment	B+	B1	B+	B+
						B	B2	B	B
						B-	B3	B-	B-
			Currently vulnerable and dependent on favorable business, financial and economic conditions to meet financial commitments	Speculative intrinsic, or standalone, financial strength, and are subject to very high credit risk absent any possibility of extraordinary support from an affiliate or a government	Very low margin for safety. Default is a real possibility	CCC+	Caa1	CCC+	C
						CCC	Caa2	CCC	
						CCC-	Caa3	CCC-	
			Highly vulnerable; default has not yet occurred, but is expected to be a virtual certainty	Highly speculative intrinsic, or standalone, financial strength, and are likely to be either in, or very near, default, with some prospect for recovery of principal and interest; or, these issuers have avoided default or are expected to avoid default through the provision of extraordinary support from an affiliate or a government	Default of some kind appears probable	CC	Ca	CC	
			Currently highly vulnerable to non-payment, and ultimate recovery is expected to be lower than that of higher rated obligations	Typically in default, with little prospect for recovery of principal or interest; or, these issuers are benefiting from a government or affiliate support but are likely to be liquidated over time; without support there would be little prospect for recovery of principal or interest	A default or default-like process has begun, or the issuer is in standstill, or for a closed funding vehicle, payment capacity is irrevocably impaired	C	C	C	
					Experienced an uncured payment default or distressed debt exchange on a bond, loan or other material financial obligation, but has not entered into bankruptcy filings, administration, receivership, liquidation, or other formal winding-up procedure, and has not otherwise ceased operating.			RD	
			Payment default on a financial commitment or breach of an imputed promise; also used when a bankruptcy petition has been filed		Entered into bankruptcy filings, administration, receivership, liquidation or other formal winding-up procedure or that has otherwise ceased business	D		D	

*https://www.spglobal.com/ratings/en/about/intro-to-credit-ratings; https://www.moodys.com/researchdocumentcontentpage.aspx?docid=pbc_79004; https://www.fitchratings.com/products/rating-definitions#about-rating-definitions

Rating Adjustments

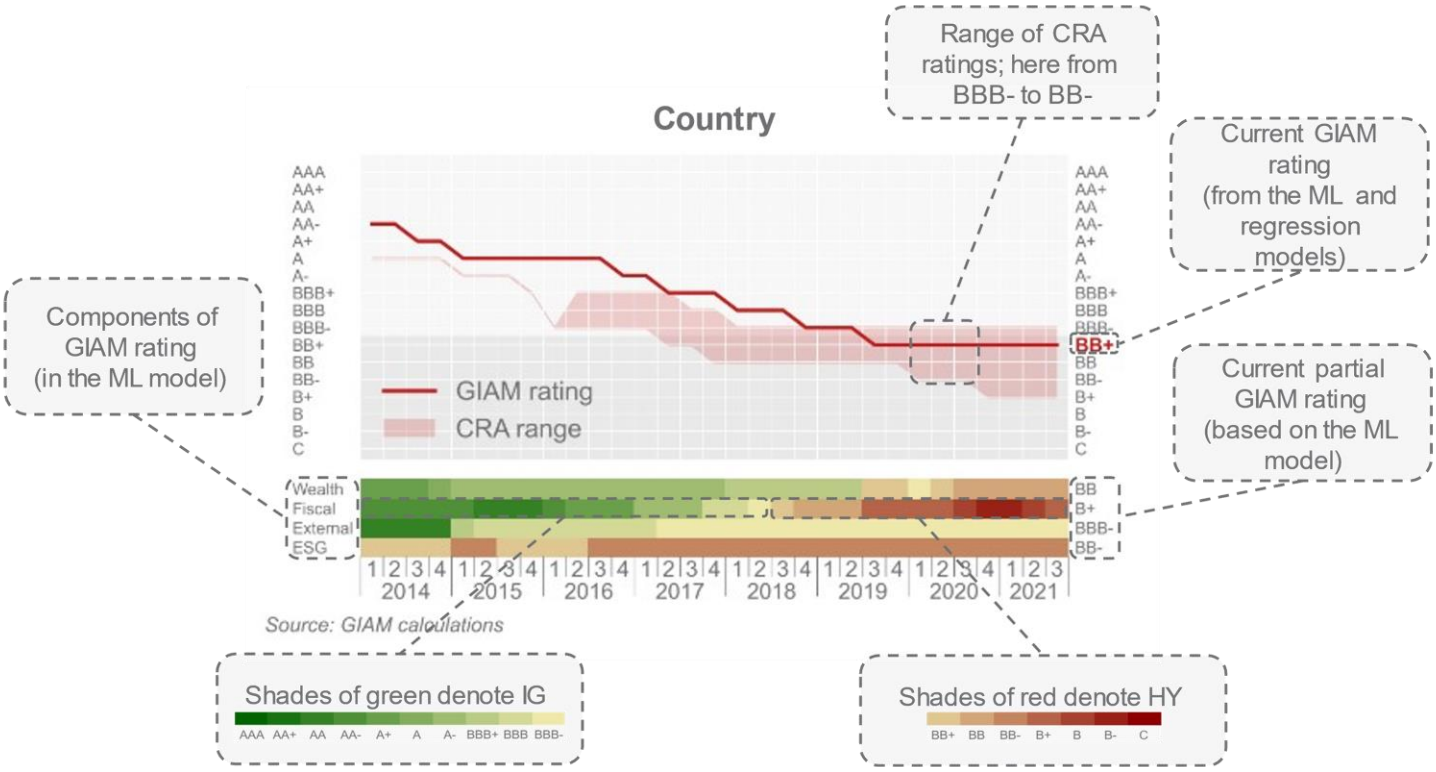
Risk Factor	Adjustment	Specification	Variable	Interpretation	Implementation	Mapping from low to high
(1) ESG	no specific adjustment					
(2) Income and Wealth	(a) income growth	median deviation from ±2 year avg sperarate for EM / AE	GDP, constant prices (%yoy) nadj	the higher, the better	quintiles	2| 1| 0|-1|-2
	(b) income growth volatility	volatility over past 10 years	GDP, constant prices (%yoy) nadj	the lower, the better	quartiles	0| 0| 0| 1
(3) Fiscal Outlook	(a) vulnerability	level	NPL (in % of Banking Sector) → A×B/C *A Dom. Credit to Priv. Sect. by Banks (% of GDP) nadj* *B Bank NPLs to Total Gross Loans (%) nadj* *C Bank Capital to Assets Ratio (%) nadj*	the lower, the better	quintiles	-2|-1| 0| 1| 2
	(b1) primary balance	3yr average	General Govt. Primary Net Lending/Borrowing (% of GDP) nadj	the higher, the better	quintiles	2| 1| 0|-1|-2
	(b2) revenue volatility	volatility over past 10 years	Revenue (% of GDP) nadj	the lower, the better	terciles	-1| 0| 1
(4) External Imbalances	(a) external debt	level	External Debt (% of GDP) nadj	the lower, the better	terciles	-1| 0| 1
	(b1) reserve currency	dummy, 1 if yes		the higher, the better	scaling	0|-2
	(b2) actively traded currency	dummy, 1 if yes		the higher, the better	scaling	0|-1
(A) Monetary Policy*	(a) credit size	level	Dom. Cedit Provided by Fin. Sect. (% of GDP) nadj	the higher, the better	quintiles	1| 2| 3| 4| 5
	(b) FX regime	dummy: 1 to 10		the higher, the better	scaling	1| 2| 3| 4| 5
(B) TooBig ToFail**	country size	level	GDP (current prices)	the higher, the better	ranking	TOP10 -1| TOP5 -2
*(C) CRA bias***	*deviation from CRA rating*	*cumulated average difference to CRA rating*				

*to be additionally applied to **(2)** and **(3)***

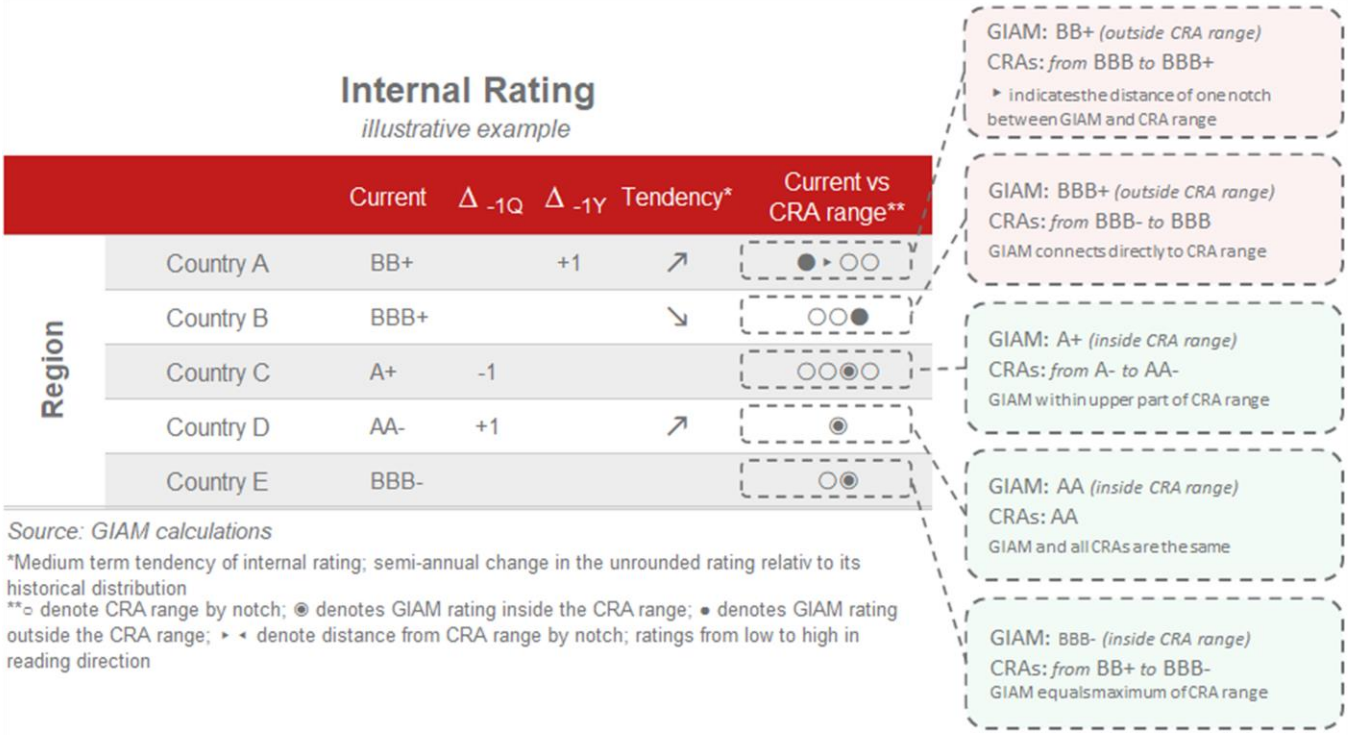
***to be applied to the final rating*

Credit Size

FX Regime	1	2	3	4	5
1	2	2	1	1	0
2	2	1	0	0	-1
3	1	0	0	-1	-1
4	1	0	0	-1	-2
5	1	0	-1	-2	-2



Range of CRA ratings; here from BBB- to BB-
Country
Current GIAM rating (from the ML and regression models)
Components of GIAM rating (in the ML model)
AAA AA+ AA AA- A+ A A- BBB+ BBB BBB- BB+ BB BB- B+ B B- C
GIAM rating
CRA range
BB+
Current partial GIAM rating (based on the ML model)
Wealth
Fiscal
External
ESG
BB B+ BBB- BB-
2014 2015 2016 2017 2018 2019 2020 2021
Source: GIAM calculations
Shades of green denote IG
AAA AA+ AA AA- A+ A A- BBB+ BBB BBB-
Shades of red denote HY
BB+ BB BB- B+ B B- C



Internal Rating
illustrative example
Current
Δ -1Q
Δ -1Y
Tendency*
Current vs CRA range**
Region
Country A BB+ +1 ↗
Country B BBB+ ↘
Country C A+ -1
Country D AA- +1 ↗
Country E BBB-
Source: GIAM calculations
*Medium term tendency of internal rating; semi-annual change in the unrounded rating relativ to its historical distribution
**○ denote CRA range by notch; ◉ denotes GIAM rating inside the CRA range; ● denotes GIAM rating outside the CRA range; ‣ ◂ denote distance from CRA range by notch; ratings from low to high in reading direction
GIAM: BB+ (outside CRA range)
CRAs: from BBB to BBB+
‣ indicates the distance of one notch between GIAM and CRA range
GIAM: BBB+ (outside CRA range)
CRAs: from BBB- to BBB
GIAM connects directly to CRA range
GIAM: A+ (inside CRA range)
CRAs: from A- to AA-
GIAM within upper part of CRA range
GIAM: AA (inside CRA range)
CRAs: AA
GIAM and all CRAs are the same
GIAM: BBB- (inside CRA range)
CRAs: from BB+ to BBB-
GIAM equals maximum of CRA range

IMPRINT

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