

Country Risk Assessment

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1	Introduction and Purpose.....	5
1.1	Limitations	5
1.2	Roles and responsibilities	5
2	Sources and data	6
2.1	Country scope.....	6
2.2	Data selection.....	6
2.3	Data attributes	6
2.3.1	EU/EES Membership	7
2.3.2	FATF Membership.....	7
2.3.3	FATF Grey and Blacklist.....	7
2.3.4	EU High Risk Third Countries (EUHR3C).....	7
2.3.5	Corruption Perception Index (CPI)	8
2.3.6	Financial Secrecy Index (FSI)	8
2.3.7	Global Terrorism Index	8
2.3.8	Global Peace Index.....	8
2.3.9	Freedom House Score.....	8
2.3.10	Open budget transparency.....	8
2.3.11	Basel AML Index	8
2.3.12	EU Tax Haven.....	9
2.3.13	EU Sanctions Map.....	9
2.3.14	OFAC - Office of Foreign Assets Control.....	9
2.3.15	HM Treasury	9
2.3.16	World map – border information.....	9
2.3.17	CEEPI – World trade data	10

3	Methodology	11
3.1	Conceptual methodology	11
4	Model design	12
4.1	Model algorithm.....	12
4.1.1	ML/TF model.....	12
4.1.2	Sanctions model.....	12
4.2	Data Types.....	13
4.2.1	Data Cleaning.....	14
4.2.2	Data normalization	16
4.2.3	Data binning.....	18
4.3	Weights.....	19
4.3.1	Weights ML/TF.....	19
4.3.2	Importance factor & adjusted weights.....	19
4.3.3	Weight and bin for sanction risk.....	22
4.3.4	Importance factor & adjusted weights.....	22
4.4	Completeness Analysis.....	23
4.4.1	Completeness analysis ML/TF.....	24
4.4.2	Completeness analysis sanction	25
4.4.3	Value if null	25
4.5	Sanctions coverage.....	26
4.6	Risk Classes and Thresholds	26
4.6.1	Threshold analysis.....	27
4.6.2	Threshold ML	27
4.6.3	Threshold TF	27
4.6.4	Threshold Sanctions.....	28
4.7	Manual overrides ML/TF.....	29
4.7.1	Greenland	29

4.7.2	The Faroe Islands	29
4.7.3	Svalbard and Jan Mayen	30
4.7.4	Åland Islands	30
4.8	Manual Overrides Sanctions.....	30
4.8.1	Norway.....	30
4.8.2	South Korea	30
4.8.3	Svalbard and Jan Mayen	31
4.8.4	Åland Islands	31
4.9	Model output	31
4.10	Data quality.....	33
4.11	Data quality controls.....	33
4.12	Data testing ML / TF	33
4.13	Data testing Sanctions.....	44
4.14	Data flow.....	45
5	Framework.....	46
5.1.1	System configuration	46
5.1.2	Follow-up	46
5.1.3	Distribution of model output.....	46
5.1.4	Validation.....	46
5.1.5	Model changes.....	47
6	Appendices	48
6.1.1	Country risk calculations.....	48
6.1.2	Completeness analysis – Missing values.....	50
6.1.3	EU Sanctions Coverage analysis.....	50

1 Introduction and Purpose

The primary objective of the country risk assessment (Hereinafter “CRA”) model is to rate the risk of Money Laundering/Terrorist Financing (hereinafter “ML/TF”) and sanctions (including circumvention) for all possible countries by assessing various factors that may be indicative of ML/TF or sanctions risk inherent to the country. This is to enable the client to comply with the Anti-Money Laundering and international sanctions requirements and assess geographical risks appropriately. This model will provide input and enhance the other models and processes, such as the transaction monitoring (hereinafter “TM”), customer risk classification (hereinafter “CRR”) and know your customer (hereinafter “KYC”)-processes. Additionally, it is recommended that the country risk assessment should be integrated into the general risk assessment framework.

1.1 Limitations

The results from the country risk assessment, including the country risk scores and grades, are provided to external clients. Frank Penny is not responsible for the correct implementation of these results in underlying models or processes and therefore cannot verify the extent to which the results have been implemented correctly. Furthermore, the customer is responsible for managing the risk of the countries from the assessment and manual adjustments to the product provided by Frank Penny.

1.2 Roles and responsibilities

Frank Penny is responsible for delivering the country risk assessment to the client in accordance with the established and signed agreement. The list will be transferred to the client using the agreed-upon method. Additionally, Frank Penny is accountable for communicating any significant changes that may impact the model's output to ensure transparency and alignment with client expectations.

Model Developer is responsible for overseeing all necessary activities within the model's lifecycle. This includes ensuring that any updates, changes, or errors are addressed promptly and communicated to the product owner. The model developer must also ensure the model remains accurate and relevant through continuous monitoring and refinement.

Product Owner is responsible for the overall management and maintenance of the product. This includes coordinating communication between the client and the model developer, as well as overseeing any major adjustments or improvements to the country risk assessment. The product owner ensures that the product remains aligned with both client requirements and internal standards.

End User (Client) is responsible for implementing the risk assessment and corresponding risk classifications within their internal systems and/or models. Frank Penny is not responsible for ensuring the correct implementation of the list in the client's dependent models and processes. It is the client's responsibility to integrate the risk assessment data properly within their operational framework.

2 Sources and data

2.1 Country scope

The model includes 250 countries and dependencies or other territories. It is important to note that the number is subject to change over time when the model is updated. The difference between a dependency and a country is that a dependency does not possess full political independence or sovereignty.

2.2 Data selection

To decide which sources to use, the extensive groundwork of checking the data quality on different reliable sources has been done. The data needs to be up to date to be classified as a high-quality source. Furthermore, it is beneficial if the data is updated on a regular basis since the model is agile and is supposed to be updated from time and time again. To be considered 'up to date,' the source should typically reflect recent information and be refreshed at regular intervals to ensure data remains current. If the data is older than two years, the source will be classified as "low quality" and will not be part of the input data. Furthermore, to be a reliable source, the data must be on a government site, or an unbiased creator of the site/data. The source should also be an established and widely recognized authority in its field to ensure credibility and trustworthiness in the data provided.

Other than being a reliable source, the data also must play an inherent role in the risk of ML, TF and sanction, i.e., be a reasonable and adequate source of information.

2.3 Data attributes

The following is a list of all the data attributes in the model with links to the source:

Data attribute	Data Source
EU/EES Membership	Countries in the EU and EEA - GOV.UK (www.gov.uk)
FATF Membership	Countries - Financial Action Task Force (FATF) (fatf-gafi.org)
FATF Grey and Blacklist	FATF Greylist & Blacklist - A Complete Guide ComplyAdvantage
EUHR3C	EU policy on high-risk third countries European Commission (europa.eu)
Corruption Perception Index	2023 Corruption Perceptions Index - Explore the... - Transparency.org
Financial Secrecy index	Introduction (taxjustice.net)
Global Terrorism Index	https://www.visionofhumanity.org/maps/global-terrorism-index
Global Peace Index	https://www.visionofhumanity.org/maps
Freedom House Score	Countries and Territories Freedom House

Open Budget Transparency	Rankings International Budget Partnership
Basel AML Index	Public Ranking - Basel AML Index (baselgovernance.org)
EU Tax Haven List	https://www.consilium.europa.eu/en/policies/eu-list-of-non-cooperative-jurisdictions/
EU Sanctions Map	https://www.sanctionsmap.eu/#/main
World map (border information)	https://nacis.org/initiatives/natural-earth/
CEPI – World trade data	https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37

2.3.1 EU/EES Membership

The European union is a union which consists of 27 member states while EES includes an additional 3 countries. To become a member of the EU, the member states are obligated to apply customer due diligence requirements when entering a business relationship. Since the EU/EES member states are required to have regulatory requirements in place to combat ML and TF, it's a good source to have when making a country risk assessment. Being a member of the EU/EES will be considered as a lower risk of AML/CTF for the country. This source is updated on a regular basis.

2.3.2 FATF Membership

The Financial action task force (FATF) members must follow their membership policy which includes a certain level of commitment to AML/CTF efforts as well as AML/CTF risks faced and efforts to combat those risks. Being a FATF member should therefore be a risk diminishing variable, just like being a member of the EU. This source is updated on a regular basis.

2.3.3 FATF Grey and Blacklist

FATF also has Grey and Blacklist. The Blacklist signifies countries or territories that are considered by the FATF to be non-cooperative in the global effort against ML and or TF. The Greylist is similar to the Blacklist, but the greylisted countries have made some commitment to improving their efforts in combating ML and TF. This list will be used to set a dominant value (hard rule), i.e., if a country is listed by the FATF on the grey or blacklist, it will automatically be assigned the highest possible risk class. This source is updated on a regular basis.

2.3.4 EU High Risk Third Countries (EUHR3C)

The EU H3RC includes a list of countries. The countries included in the list are deemed to have a high risk of AML/CTF probability, and therefore the list exists to protect the financial systems from risk associated with these countries. There is a new directive that forces banks and other gatekeepers to be more vigilant in their approach to the countries included in the list. Therefore, much like the FATF grey and blacklist, countries on the EUHR3C list will automatically be considered as the highest possible risk for AML/CTF. This source is updated on a regular basis.

2.3.5 Corruption Perception Index (CPI)

This source is about exposing systems and networks that enable corruption to thrive. The goal of the index is to penalize countries that have persistently high corruption and to improve transparency worldwide. Since corruption is a significant driver of ML globally, this index serves well as an indicator for increased ML risk. Therefore, a high CPI correlates with a higher risk of ML. This source is updated on a yearly basis.

2.3.6 Financial Secrecy Index (FSI)

The FSI ranks countries (or jurisdictions) offshore activities and secrecy. The FSI aims to assess for example tax havens. A tax haven offers individuals, business, and criminals no tax liability for their bank deposits. Since this is an increase in the risk of ML, this variable will determine that the higher the FSI score, the higher the risk of ML. This source is updated on a regular basis.

2.3.7 Global Terrorism Index

The global terrorism index analyses countries for the impact of terrorism in respectively country. It uses data from different sources like Terrorism Tracker. This is the only source, which is truly linked to terrorism, which makes it an important addition to the list of variables. A high score on the GTI means a higher risk for TF which leads to a higher risk of ML. This source is updated on a yearly basis.

2.3.8 Global Peace Index

Much like the global terrorism index, the global peace index measures the persevering level of peace in a country. It is the world's leading measure of peacefulness. They measure the level of societal safety, the degree of militarization, the extent of ongoing domestic and international conflict to name a few. If a country has a high peace index, the variable will guide the decision making into that there's a lower risk of ML. This source is updated on a yearly basis.

2.3.9 Freedom House Score

The Freedom House measures how much political rights, and civil liberties countries have. If a country lacks political rights and civil liberties basically means that it has a higher risk of corruption and other destructive economic and social behavior. Therefore, it is believed that a high degree of freedom is correlated to a lower risk of TF. Thus, a high FHS score indicates that the country is less likely to finance terrorism. This source is updated on a regular basis.

2.3.10 Open budget transparency

The open budget transparency measures the trust in society that people's views and interests are respected, and that the public money is used well. A high value in the open budget transparency means that the country is transparent towards the world economy and is therefore less likely to exhibit ML. This source is updated on a yearly basis.

2.3.11 Basel AML Index

The Basel AML Index measures each country's likelihood of ML and includes sources that are also present in the model. It determines the measure based on factors such as the quality of the ML framework, bribery and

corruption, and legal and political risks, among others. The index serves as a valuable indicator of increased ML risk and is updated annually.

2.3.12 EU Tax Haven

The EU Tax Haven List, officially known as the EU List of Non-Cooperative Jurisdictions for Tax Purposes, identifies countries that do not meet international tax transparency and fairness standards. Countries placed on this list are deemed to facilitate harmful tax practices, creating a higher risk environment for money laundering (ML) and tax evasion. The list is regularly updated by the EU Council based on assessments of transparency, fair taxation, and compliance with international standards

2.3.13 EU Sanctions Map

The EU Sanctions Map is a comprehensive resource that provides an overview of all sanctions adopted by the European Union against countries, organizations, or individuals. These sanctions can include economic restrictions, trade embargoes, asset freezes, and travel bans, and are implemented to combat issues like terrorism, corruption, and violations of international law.

This source serves a dual purpose within the broader risk assessment framework. First, in line with guidance from external bodies such as the Wolfsberg¹ that assess that regulators generally expect that financial institutions apply the highest levels of due diligence for customers connected to sanctioned countries. But also to calculate the sanction risk and circumvention in the sanction risk model.

2.3.14 OFAC - Office of Foreign Assets Control

OFAC (Office of Foreign Assets Control), part of the U.S. Department of the Treasury, administers and enforces economic and trade sanctions. These include asset freezes, restrictions on financial transactions, and prohibitions on business activities with sanctioned entities. The U.S. enforces these measures under multiple regimes such as the Specially Designated Nationals (SDN) List, which targets individuals, entities, and governments identified as threats to U.S. foreign policy and national security.

2.3.15 HM Treasury

The Office of Financial Sanctions Implementation (OFSI), a unit of HM Treasury in the United Kingdom, oversees the enforcement of sanctions within the UK. It works to ensure that UK financial institutions and businesses comply with both domestic and international sanctions, including those imposed by the United Nations, the EU, and the U.S. Through sanctions, OFSI aims to counter terrorism, human rights violations, and financial crimes.

2.3.16 World map – border information

The World Map – Border Information layer provides geopolitical insights relevant to assessing sanction risks and the potential circumvention of international sanctions. Countries with proximity to sanctioned jurisdictions may present an elevated risk of sanction evasion. Border regions are often exploited for illicit trade routes, making them critical to monitor in the context of cross-border financial flows and customer geolocation data. This

¹ [https://db.wolfsberg-group.org/assets/6a3513cd-b486-4d7e-aa2f-698b18ed05fb/Wolfsberg%20Group%20Country%20Risk%20FAQs%20\(2024\).pdf](https://db.wolfsberg-group.org/assets/6a3513cd-b486-4d7e-aa2f-698b18ed05fb/Wolfsberg%20Group%20Country%20Risk%20FAQs%20(2024).pdf)

information supports risk assessments by identifying jurisdictions where goods or capital may transit in violation of international sanctions regimes. Due to the purpose of including the factor in the sanctions model, only land borders will be assessed as a boarder.

2.3.17 CEEPI – World trade data

The CEEPI World Trade Data layer offers global trade flow analytics that help assess risks related to sanctions circumvention. Trade volumes between jurisdictions, particularly involving sanctioned countries or high-risk partners, are key indicators for identifying possible indirect sanction breaches. For example, increased exports from a neutral country to a sanctioned country via a third-party hub may signal attempts to bypass export restrictions. This dataset supports the detection of atypical trade routes and facilitates the identification of entities potentially involved in the evasion of international sanctions.

3 Methodology

The selected methodology was ultimately chosen based on the model's purpose, the nature of the data, and operational constraints. By carefully weighing these elements, it is possible to ensure that the model aligns with both theoretical requirements and practical limitations. The following section outlines the chosen methodology.

3.1 Conceptual methodology

The methodology is grounded in industry best practices and robust statistical principles, tailored to align with the structure and characteristics of the underlying data sources. The model uses a weighted scoring framework, where each risk factor (i.e., data source) is assigned a value and a corresponding weight that reflects its relative significance. This allows the model to prioritize higher-risk indicators while maintaining a comprehensive assessment of the broader risk environment. Final risk scores are calculated as aggregates of normalized, weighted values.

This methodology was deliberately designed for clarity and simplicity, ensuring transparency in its logic and ease of future adjustments. Its straightforward structure enhances adaptability, allowing for seamless integration of evolving data inputs or changing regulatory expectations.

While the underlying methodological approach remains consistent, the model is applied separately to assess money laundering/terrorist financing (ML/TF) risk and sanction risk. Where significant changes have been made it will be addressed in a distinct section of the documentation, reflecting their differing regulatory frameworks, data inputs, and risk indicators. The following sections will provide further detail on the specific model structures, scoring logic, and implementation for both ML/TF and sanction country risk assessments.

4 Model design

The model design, as described in the previous section, is a weighted scoring model. This means that each risk factor (source) is assigned both value and weight. However, since the values from different sources vary in format and range, certain mathematical normalizations are required before the model calculations can be executed. These normalizations ensure that the data is comparable and that the model produces accurate results. The overall dataflow is relatively straightforward: data is collected from external sources, cleaned, and processed for risk assessment. The resulting outputs are then delivered to customers, who are responsible for applying the model within their specific use cases.

The following sections will detail the various steps involved in this process.

4.1 Model algorithm

A brief introduction to the practical workings of each model will be provided in the following sections. However, for a comprehensive understanding of the inputs, algorithms, and outputs, the full model documentation must be reviewed.

4.1.1 ML/TF model

An additive model is used for ML/TF risk calculations, where each risk factor is first normalized and then multiplied by a corresponding weight. These weighted factors are subsequently aggregated to produce the final risk score. Dominant risk aspects fall outside this additive framework and are applied separately in a post-calculation step to adjust the overall risk assessment. The final formula is as follows:

$$\sum_{i=1}^X AW_x * RF_x$$

AW = Adjusted weight for each risk factor

RF = Input from each risk factor

Assumptions: $RF \in [0,1]$

4.1.2 Sanctions model

Calculating sanction risk is more complex than ML/TF risk due to interdependencies between factors. Initially, the sanction risk is determined by first identifying whether a country is sanctioned and then evaluating the extent of those sanctions, for example, by considering how many restrictive measures have been imposed on that country. This sanction risk factor is then used as an input when assessing trade and bordering risks, which rely on sanction risk in their calculations. Once these assessments are completed, the resulting scores are aggregated, similar to the ML/TF approach, to produce a final overall risk score. The final formula is as follows:

$$W_1 * S + W_2 * f(S, T) + W_3 * f(S, B) + W_4 * FS = \text{Country sanction risk}$$

S = Sanction and to what extent

T = Trade

B = Bordering country

FS = Financial secrecy

f(S, T) = Function of trade to sanctioned countries

$f(S, B)$ = Function of bordering to sanctioned country

W_x = Weight for each riskfactor

Assumptions: $f(S, T)$, $f(S, B)$, $FS \in [0,1]$

4.2 Data Types

The model has 14 sources; these sources have different types of possible outcomes for the values. Due to this, the sources can be divided into three groups of data types, contingent on their possible outcomes.

1. Binary variables – A binary variable can only take two values, for example yes or no.
2. Ordinal variables – A ordinal variable is much like a categorical variable but with the difference that an ordinal variable has a clear ordering for categories.
3. Real-Valued multiplicative variables – A variable whose values are real, which includes natural numbers, whole numbers, integers, rational numbers, irrational numbers.

The table below shows which data type each attribute belongs to:

Data attribute	Data Type
EU/EES Membership	Binary variable
FATF Membership	Binary variable
FATF Grey and Blacklist	Binary variable
EUHR3C	Binary variable
EU Sanctions Map	Ordinal variable
OFAC/OFSI sanction regimes	Ordinal variable
Corruption Perception Index	Real-Valued multiplicative variable
Financial Secrecy index	Real-Valued multiplicative variable
Global Terrorism Index	Real-Valued multiplicative variable
Global Peace Index	Real-Valued multiplicative variable
Freedom House Score	Real-Valued multiplicative variable
Open Budget Transparency	Real-Valued multiplicative variable
Basel AML Index	Real-Valued multiplicative variable
EU Tax Haven	Real-Valued multiplicative variable
Bordering countries	Binary variable

Trade data	Real-Valued multiplicative variable
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4.2.1 Data Cleaning

Since the data comes from various sources and includes different data types, it needs to be cleaned to ensure a fair and accurate rating. If the data is not properly cleaned, certain sources may have a disproportionate impact on the result. For example, a source with a highly skewed distribution could cause an imbalance, where its top value influences the outcome more than intended. Additionally, the data from different sources can vary significantly in format—some sources provide text values, some offer a continuous range of numbers, some are restricted to a fixed set of outcomes, and others may be binary.

To achieve meaningful analysis and consistent results, the data must be standardized. The method employed in this case is to normalize every attribute to a value between 0 and 1. This ensures that all sources are comparable, regardless of their original format or scale, and prevents any single data source from unduly influencing the results. It is important to note that infinite does not always imply that a source can take a value between 1 and infinite, it can also imply that a source can have an infinite number of decimals. In theory there are an infinite number of values between 1-100, if there are no limitations to formatting. This is just for clarification; the number of possible values have no direct effect on the model or the outcome.

The table below illustrates the possible number of assigned values for each attribute:

Data attribute	Number of possible values assigned
EU/EES Membership	2
FATF Membership	2
FATF Grey and Blacklist	2
EUHR3C	2
Corruption Perception Index	100
Eu Tax	2
Financial Secrecy index	Infinite
Global Terrorism Index	Infinite
Global Peace Index	Infinite
Freedom House Score	100
Open Budget Transparency	100

Basel AML Index	infinite
EU Tax Haven	5
Bordering countries	2
Trade data	infinite
EU Sanctions	64
OFAC/OFSI sanction regimes	2

Below tables show the value range of the data variables

Data type binary variable:

Data attribute	Value if false	Value If true
EU/EES Membership	FALSE	TRUE
FATF Membership	FALSE	TRUE
EUHR3C	FALSE	TRUE
FATF Grey and Blacklist	FALSE	TRUE

Data type Real-Valued multiplicative variable:

Data attribute	Min value	Max Value
Corruption Perception Index	0	1
Financial Secrecy index	0	100
Global Terrorism Index	0	10
Global Peace Index	0	5
Freedom House Score	0	100
Open Budget Transparency	0	100
Basel AML Index	0	10
EU Tax Haven	0	4

Bordering countries	0	1
Trade data	0	2 ²
EU sanctions	0	64
OFAC/OFSI sanction regimes	0	1

4.2.2 Data normalization

To be able to correctly and efficiently estimate risk classifications the input data must be normalized and standardized. Therefore, the objective is to assign all the variables a value between 0 and 1. To do this, the following methods are employed:

- Normalize data
- Translating text into numbers – is a quite straightforward procedure since the text, for this model, is only binary (yes/no) which simplifies the translation.

The table below shows which attribute will be used with the above method:

Data attribute	Value
EU/EES Membership	Translate text into numbers
FATF Membership	Translate text into numbers
FATF Grey and Blacklist	Translate text into numbers
EUHR3C	Translate text into numbers
OFAC/OFSI sanction regimes	Translate text into numbers
Corruption Perception Index	Normalize
Financial Secrecy index	Normalize
Global Terrorism Index	Normalize
Global Peace Index	Normalize
Freedom House Score	Normalize
Open Budget Transparency	Normalize
Basel AML Index	Normalize

² Trade data is aggregated on export and import percentages, for each underlying

EU Tax Haven	Normalize
Trade data	Normalize
EU Sanctions	Bin

The binary variables need to be translated into the following:

Data attribute	Value if false	Value If true
EU/EES Membership	1	0
FATF Membership	1	0
EUHR3C	0	1
FATF Grey and Blacklist	0	1

The reason the binary values differ is because EU/EES membership and FATF memberships is meant to be a positive outcome and EUHR3C and FATF Grey and Blacklist is meant to be a negative outcome, i.e., if a country is EUHR3C it's going to have a higher risk of ML/TF.

The normalization formula in this case looks like this if a high value leads to a high score (i.e. negative outcome):

$$y_i = (x_i - \min(x)) / (\max(x) - \min(x))$$

And like this if a low value corresponds to a high score (negative outcome):

$$y_i = (\max(x) - x_i) / (\max(x) - \min(x))$$

The reason for this is that different indices interpret scores in varying ways. For instance, on the Financial Secrecy Index, a high score indicates significant secrecy, warranting a high ML score as a penalty. Conversely, on the Corruption Perception Index, a high score reflects low corruption, hence the correct formula needs to be applied to ensure that low scores result in a high ML score.

Data attribute	Min value	Max Value
Corruption Perception Index	0	1
Financial Secrecy index	0	1
Global Terrorism Index	0	1
Global Peace Index	0	1
Freedom House Score	0	1

Open Budget Transparency	0	1
Basel AML Index	0	1
EU Tax Haven	0	1
Bordering	0	1
EU Sanction ³	1	1,75
OFAC/OFSI sanction regimes	0	1

4.2.3 Data binning

Restrictive measures implemented by the EU vary significantly between countries. For example, there are 64 active restrictive measures targeting Russia, while only one active measure—an arms embargo—is currently applied to China. This indicates that the risk of sanction violations is arguably higher in trade or transactions involving Russia compared to China. However, both countries remain subject to active restrictive measures.

To accurately capture these nuances, the model output reflects two key aspects: whether a country is sanctioned at all, and the extent of those sanctions. To represent this, a set of bins has been introduced to quantify the scope of sanctions:

- 1: The country is sanctioned, regardless of the extent.
- 0 to 0.75: An additive value that scales based on the severity and breadth of the sanctions imposed on the country.

This approach allows the model to differentiate risk levels more precisely depending on both the presence and the intensity of sanctions. The following table presents the thresholds and bins to represent the scope of the restrictive measures. It shall be noted that this does not imply that 1 sanction implies a low risk for the country, as presented in the threshold section these countries are still at high risk but to a lower extent compared to the highest bin.

Number of restrictive measures (threshold)	Extent of sanction (bin)
More than 10	1,75
More than 4 but less than 10	1,5
More than 2 but less than or equal to 4	1,25
Less than or equal to 2	1

³ The EU Sanction variable takes a value between 1.00 and 1.75, where 1.00 indicates that a country is subject to EU sanctions, and values above 1.00 reflect the increasing severity or breadth of those sanctions.

4.3 Weights

To ensure that both the ML/TF and sanction output is aligned with internal expectation, a certain adaptation to the underlying weights must be performed. This is since certain variables or risk factors vary depending on quality of data, quality of proxy, average values and general effectiveness of the variable.

4.3.1 Weights ML/TF

There are 10 sources that are included in the calculations that are not classified as hard rules. Five of the sources are connected to TF and seven are connected to ML. Therefore, initially the following weights are assigned, with each source having the same weight based on the total number of sources:

Data attribute	Weight	Type
EU/EES Membership	1/7	ML
FATF Membership	1/7	ML
EU/EES Membership	1/5	TF
FATF Membership	1/5	TF
Corruption Perception Index	1/7	ML
Financial Secrecy index	1/7	ML
Global Terrorism Index	1/5	TF
Global Peace Index	1/5	TF
Freedom House Score	1/5	TF
Open Budget Transparency	1/7	ML
Basel AML Index	1/7	ML
EU Tax Haven	1/7	ML

4.3.2 Importance factor & adjusted weights

Based on an expert opinion, the sources should not have an equal importance on the outcome of the model as they impose a vast distribution of possible outcomes. Therefore, an importance factor is included in the calculations which influences the adjusted weight. It is important to note that, regardless of the weight or impact a source has on the outcome, all sources in the model remain highly relevant. Non-relevant or important lists have not been included in the model since they have not fulfilled the selection criteria.

The following concepts are considered when weighing the variables:

1. Hard rules – Some of the sources are intended to give direct answers, and if a country is hit by any of the hard rules a fixed minimum risk class for that country will be set.
2. How many countries are included in the source – If a source lacks a lot of data, it will be penalized accordingly by getting a lower weight.
3. Expert opinion – With extensive experience within the field of ML and RF, there is a strong understanding of what to value and therefore how important a list should be

The following hard rules are applied:

- If a country is blacklisted by the FATF, it will automatically be set to “Very High”
- If a country is greylisted by the FATF, it will automatically be set to “Very High”
- If a country is classified as a EUHR3C then it’s automatically set to “Very High”
- If a country is classified sanctioned by the EU, then it’s automatically set to “High”

The importance factor is initially set to 1 which indicates that every source is as valuable as each other. For example, set the “Importance factor” to 1,25 implies that that source is $\frac{1,25}{1} - 1 = 0,25 = 25\%$ more valuable than the source that it valued the least. When the importance factor is included, the new weight is estimated via:

$$Adjusted\ Weight_i = \frac{Importance\ Factor_i}{\left(\frac{sum(Importance\ Factor)}{Count(Number\ of\ attributes\ in\ type)} \right)} * Weight_i$$

Importance	Value	Description
Very important	1,25	This implies that a source is 25% more valuable than if the source is classified as “Important”
Moderately important	1,125	This implies that a source is 12,5 % more valuable than if the source is classified as “Important”
Important	1	This is the baseline

Data attribute	Importance	Reason
EU/EES Membership	Very Important	EU/EES membership requires adherence to strict AML regulations and directives. The importance of 1.25 acknowledges the comprehensive nature of EU AML frameworks, which significantly enhances a country's anti-money laundering capabilities.
FATF Membership	Very Important	The FATF sets global standards to prevent ML. Membership indicates compliance with these

		standards, which is critical for robust AML measures. A high importance of 1.25 reflects the strong influence of FATF membership on a country's ability to combat ML
Corruption Perception Index	Very Important	The Corruption Perceptions Index is a measure of the perceived level of public sector corruption. High levels of corruption can facilitate ML, so a higher importance (1.25) is warranted as lower corruption indicates stronger AML controls.
Financial Secrecy index	Important	The Financial Secrecy Index assesses the level of financial secrecy in a jurisdiction. While important, it is given a lower importance (1) compared to FATF and EU/EES membership because it focuses more on financial transparency rather than direct regulatory actions.
Global Terrorism Index	Very Important	This index measures the impact of terrorism globally. It directly relates to the threat and extent of terrorism, which is critical for understanding and combating RF. A high importance of 1.25 reflects its direct relevance.
Global Peace Index	Important	The Global Peace Index measures the relative peacefulness of countries, indicating areas of potential conflict where TF might thrive. While important, its direct influence on countering TF is indirect, so an importance of 1 is suitable.
Freedom House Score	Important	This score measures political rights and civil liberties. While it provides insight into the governance environment, its direct impact on TF is less pronounced than regulatory measures. An importance of 1 reflects this.
Open Budget Transparency	Important	Open Budget Transparency reflects how openly a government manages its budget. Transparency can deter ML by reducing opportunities for illicit financial flows. However, its direct impact on AML is somewhat less, so an importance of 1 is appropriate.
Basel AML Index	Moderately important	The Basel AML Index evaluates the risk of ML and TF. It provides a comprehensive risk assessment, which is vital for improving AML strategies. An importance

		of 1.125 reflects its moderate but significant influence.
EU Tax Haven	Important	The EU list of non-cooperative jurisdictions for tax purposes is part of the EU's work to fight tax evasion and avoidance. It is composed of countries which have failed to fulfil their commitments to comply with good tax governance criteria within a specific timeframe, and countries which have refused to do so.

4.3.3 Weight and bin for sanction risk

As introduced in Section 4.1.2, the model utilizes specific input variables to calculate trade and border exposure to certain sanction risks. Consequently, the overall weighting differs slightly from that used in ML/TF risk assessments. Four variables are employed to calculate sanction risk: one variable captures the restrictive measures implemented by the EU, representing the direct sanction risk, while the other three variables reflect the risk of circumventing these restrictive measures. The table below presents the weights assigned to each variable along with the rationale behind their selection.

Variable	Motivation for inclusion	Weight	Motivation for weight
EU Sanction/OFAC/OFSI sanction regimes	Used to estimate actual sanction risk with country	1	Similar to dominant factors in ML/TF, the sanction risk will be included in its entirety to represent the actual sanction risk
Trade with sanctioned party	Proxy for circumvention of restrictive measure	1/3	Initial weights will be that of equal distribution.
Bordering with sanctioned party		1/3	
Financial secrecy index		1/3	

4.3.4 Importance factor & adjusted weights

Like the assumption applied in the ML/TF risk model, and based on expert judgement, it is acknowledged that the data sources used in the sanctions model do not carry equal importance in influencing the model's outcome. This is due to the broad variance in nature and impact of these sources. As a result, an importance factor is applied during the weighting process to adjust the influence of each source proportionally to its significance.

It is important to emphasize that all included sources remain highly relevant to the model's assessment. Any

sources deemed non-essential or lacking in reliability or relevance have been excluded from the model, as they did not meet the defined selection criteria.

What distinguishes the sanctions risk model from the ML/TF model is that it incorporates a different number of input variables, and several of these variables are interdependent. For example, the EU/OFAC/OFSI sanction sanctions variable not only reflects direct sanction status but also influences other factors, such as trade and bordering risks.

Trade is treated as a direct indicator of potential circumvention of restrictive measures, while bordering risk captures the potential for unreported or informal trade, including smuggling. It is generally reasonable to assume that neighboring countries engage in some level of trade. However, the model does not currently account for the actual openness or permeability of borders. For instance, despite the border between South and North Korea being one of the most closed in the world, which may motivate a lower weight in the model. This limitation is recognized and further addressed in the manual override section.

Finally, the financial secrecy variable addresses the limitations of self-reported trade data. Countries with lower transparency and limited access to financial information may present a higher risk, as they can be more attractive to sanctioned entities seeking to obscure their activities. This factor helps account for underreporting and systemic opacity in international trade flows.

To further enhance model accuracy, the original equal weighting approach ($\frac{1}{3}$ per factor) has been recalibrated to reflect the observed variation in factor distributions and their respective relevance to sanctions risk. The revised weights are:

- Trade: 0.5
- FSI: 0.4
- Bordering: 0.1

By assigning a lower weight to bordering factor, we better align its contribution with its practical relevance. In contrast, Trade and FSI serve as more reliable and direct proxies for real-world sanction risk, justifying their greater influence in the model.

It is important to reiterate that this recalibration does not imply any factor is irrelevant. Rather, it enhances the model's ability to differentiate risk appropriately by ensuring that each factor contributes in proportion to its analytical value.

Variable	Initial weight	New weight
Trade	1/3	0,5
Bordering	1/3	0,1
Financial secrecy	1/3	0,4

4.4 Completeness Analysis

Before risk factors can be considered robust and relevant, the quality and completeness of underlying data

sources must be thoroughly evaluated. Completeness is a critical factor in determining the reliability of model inputs, especially when working with global datasets that vary significantly in scope, methodology, and data collection standards.

To address this, a two-part completeness analysis was conducted: one focusing on the input sources used in the ML/TF model, and the other on the sanctions risk model. Both assessments aimed to quantify the extent of missing data across countries.

The analysis also helps highlight where the model may require fallback logic or conservative assumptions in cases of incomplete data. Additionally, comparing completeness across different input sources and models reveals recurring gaps, often concentrated among small territories, jurisdictions with limited international engagement, or those excluded by design from global indices. These insights directly inform the development of "if missing" logic, ensuring the model remains reliable and interpretable even when data is not fully available.

4.4.1 Completeness analysis ML/TF

The completeness of the underlying sources varies, so an analysis was conducted to assess the quality and completeness of each list. This involved examining the number of 'null' or missing values in each list relative to the total number of countries.

Values	N. Countries	N. Missing	Completeness
Corruption Perception Index	250	70	72%
Financial Secrecy Index	250	109	56.4%
Global Terrorism Index	250	79	68.4%
Global Peace Index	250	79	68.4%
Freedom House Score	250	55	78.0%
Open Budget Transparency	250	128	49.4%
EU Tax Haven	250	0	100%
Basel AML Index	250	89	64.4%

This test highlights that not all sources are fully complete, as they apply different selection criteria for the countries included. However, it's important to note that the missing countries are not necessarily the same across all lists. By analyzing the number of 'null' or missing values by country, rather than by list, valuable insights emerge on how frequently a country is omitted from various lists. The analysis focuses on seven lists, excluding four that are binary and therefore not relevant to this test. While most countries are missing from only one list, it is notable that 34 countries are absent from all seven lists. This underscores the need for the model to incorporate comprehensive and structured 'if missing' logic, which will be detailed in the next section. It is worth noting that the 34 countries absent from all seven lists typically have very small populations and minimal geographical areas. A few examples include Vatican City, Western Sahara, Tokelau, Sint Maarten, and Antarctica. A complete list of these countries can be found in Appendix 7.2.

N. missing	N. Countries
1	38
2	45

3	34
4	15
5	5
6	23
7	34

4.4.2 Completeness analysis sanction

The completeness of the underlying sources varies, so an analysis was conducted to assess the quality and completeness of each list. This involved examining the number of 'null' or missing values in each list relative to the total number of countries.

Values	N. Countries	N. Missing	Completeness
Financial Secrecy Index	250	109	56.4%
Trade data	250	26	89,6%
Bordering	250	0	100%

The test reveals that trade data is missing for 26 countries or territories. These are generally smaller jurisdictions, such as Monaco, Åland, Antarctica, and Saint Martin, and their absence aligns with patterns observed in the ML/TF model's completeness analysis. This suggests a consistent correlation between territorial size or status and gaps in available trade data.

4.4.3 Value if null

Determining how to handle missing values when a variable observation outcome is null is based on expert judgment. It is assumed that a lack of data could indicate an increased risk factor if a country has not been analyzed or assessed in any other external lists. Therefore, countries with missing data are penalized. This approach is grounded in the belief that countries either failing to provide adequate data to the global community or those too small to be considered relevant by certain sources should be appropriately penalized. As a result, providing reliable data is crucial, and countries with significant data gaps are automatically classified into a higher risk category. Therefore, a dynamic high value is estimated when a country is missing from a list. The 3rd quartile is taken from every observation as a null value if a high value corresponds to a negative outcome and the 1st quartile if a high value corresponds to a positive value, i.e.

$$NULL = Third\ Quartile_i = \left(\frac{3(n+1)}{4} \right)^{th} term$$

→ iff a high source value corresponds to a negative outcome

$$NULL = First\ Quartile_i = \left(\frac{(n+1)}{4} \right)^{th} term$$

→ iff a high source value corresponds to a Positive outcome

It is important to note that countries missing from a high number, or even all, of the lists, are unlikely to have a significant impact on the client's customer base, as it is improbable that any customers will have a connection to

these countries. In the rare instance that a connection does exist, it would be reasonable to assign those customers a higher risk value.

4.5 Sanctions coverage

To ensure that the model adequately incorporates sanctions risk, a correlation analysis has been performed against other relevant financial sanction lists, including FINCEN 311, OFAC, and HM Treasury. The results of this analysis, detailed in Appendix 7.3. It should be noted that the ML/TF and Sanction risk output is based on EU/UN/OFAC/OFSI sanction. If a country is included on several lists, it still only accounts for a very high risk.

4.6 Risk Classes and Thresholds

The threshold for ML and TF risks are defined based on expert knowledge and a “inside/outside” logic, i.e., analyzing the last country to be included/excluded in a risk class. This approach leverages the insights and experience of domain experts to ensure a more accurate and relevant risk assessment, capturing the complexity of each country's unique situation.

Expert judgment allows for the consideration of a wide array of nuanced, context-specific factors that quantitative models might overlook. Each country presents a unique set of challenges and circumstances that can significantly impact its ML and TF risk levels. By relying on expert judgment, it can be ensured that risk assessments reflect these complexities.

The process of defining thresholds through expert judgment involves the collaboration of multiple experts. This collective approach ensures that diverse perspectives and areas of expertise are considered, leading to a more comprehensive assessment. Once initial thresholds are proposed, they undergo a rigorous peer review process, involving discussions and deliberations among the experts to address any discrepancies and refine the thresholds. The aim is to reach a consensus that enhances the reliability and robustness of the defined thresholds.

Expert judgment allows for the thresholds to be dynamically adjusted in response to new information or changes in the global environment. This flexibility ensures that the risk assessment model remains current and effective in addressing emerging threats.

Using expert judgment to set thresholds for ML and TF risks is a sound and effective approach. It enables a nuanced, flexible, and comprehensive risk assessment that considers both quantitative and qualitative factors. By aligning with industry standards and involving multiple experts, the method ensures robust, credible, and adaptive risk classifications that reflect the complexities of the global landscape.

The strategy employed was an iterative process. The approach involved testing different thresholds and analyzing the results by identifying which countries were closest to the threshold limits. The thresholds were adjusted continuously until the desired level of satisfaction was reached, meaning until all countries were classified into appropriate risk categories.

Measure	Low	Medium	High
ML	0	0,359	0,625

TF	0	0,327	0,5996
Sanction	0	0,0547	0,1325

4.6.1 Threshold analysis

When a threshold is estimated, as detailed in the previous chapter, comprehensive analysis is performed to ensure that each country has a correct risk classification that is in line with expert judgement. During this phase a “just inside”/“just outside” analysis is performed that analyzes the countries that are just excluded or included in a risk classification. The analysis displays the countries that fall outside or are just included in the risk interval. I.e., the last country that is assessed as high risk, medium risk and low risk for both TF and ML. Thereafter, an expert opinion is performed to ensure that the countries that are close to the interval are estimated correctly. The results for a lower or higher threshold are simple that countries that are close to the interval will be included in the higher/or lower risk group.

4.6.2 Threshold ML

The latest threshold analysis for ML was performed on 2024-12-17:

Measure	Score	Risk classification	Expert judgement
Jordan	0,6295	High	OK
Barbados	0,6258	High	OK
San Marino	0,6245	Medium	OK
Andorra	0,6183	Medium	OK
...
Slovakia	0,3771	Medium	OK
Poland	0,3702	Medium	OK
The Czech Republic	0,3575	Low	OK
Estonia	0,3308	Low	OK

4.6.3 Threshold TF

The latest threshold analysis for TF was performed on 2024-12-17:

Measure	Score	Risk classification	Expert judgement
Barbados	0,6031	High	OK
The Russian Federation	0,6006	High	OK

Kosovo	0,5993	Medium	OK
Armenia	0,5979	Medium	OK
...
Argentina	0,3326	Medium	OK
Malaysia	0,3288	Medium	OK
Singapore	0,3260	Low	OK
Cyprus	0,3166	Low	OK

4.6.4 Threshold Sanctions

The sanctions risk model differs slightly from the ML/TF framework, as it is not primarily intended to follow a risk-based approach. Instead, the objective is to ensure that the sanctions risk is fully covered.

As previously discussed, there are two key dimensions to consider:

1. Whether a country is subject to EU/UN sanctions.
2. Whether there is a high risk of circumvention of sanctions involving that country.

The model is structured as follows:

- All countries that are sanctioned by the EU, UN, OFAC or OFSI are automatically assessed as very high risk from a sanction's compliance perspective.
- All remaining countries are assessed solely based on their risk of circumvention, with risk levels ranging from low to high.
 - A high circumvention risk does not imply that restrictive measures are in place, but rather that the country maintains strong ties or connections to sanctioned jurisdictions, increasing the risk of circumvention.

The latest threshold analysis for sanction was performed on 2025-11-20, a change in the threshold analysis was performed due to a national update. it shall be noted that there is an internal calculation within each risk class, i.e., in the table below Latvia and El Salvador are the two countries with the highest score in the medium risk category compared to Cayman and British virgin island which are assessed with the lowest score in the specific category.

Measure	Score	Risk classification	Expert judgement
Nicaragua	0,4788	Very High	OK

Bosnia and Herzegovina	0,4744	Very High	OK
Armenia	0,2757	High	OK
Mongolia	0,2693	High	OK
...
South Africa	0,1300	High	OK
United Arab Emirates	0,1276	High	OK
Latvia	0,1272	Medium	OK
El Salvador	0,1268	Medium	OK
...
British Virgin Islands	0,055653	Medium	OK
The Cayman Islands	0,054736	Medium	OK
Saint Helena Island	0,0597	Low	OK
Montserrat	0,0593	Low	OK

4.7 Manual overrides ML/TF

In Section 4.5.1 of the model documentation, a null analysis was conducted on countries, dependencies, and other territories to assess the coverage of relevant external source data. However, certain entities included in this analysis are not featured on any relevant watchlists or risk indices, leading to gaps in available data and assessing certain countries as high risk. Due to this lack of information, a manual override has been applied to change their risk from high to low for both ML and TF. The dependencies and territories affected by this override are as follows, with reasoning:

4.7.1 Greenland

Greenland, a self-governing territory within Denmark, has minimal economic activity, low population density, and limited financial infrastructure. It is not a hub for significant international trade or financial transactions, reducing its exposure to AML and TF risks. Moreover, it is under Danish regulatory oversight, which adheres to stringent AML/TF frameworks.

4.7.2 The Faroe Islands

The Faroe Islands, another autonomous region under Danish sovereignty, also exhibits limited financial activity on an international scale. Its economic activity is primarily centered around fisheries and local trade, both of

which are closely regulated. Similar to Greenland, the Faroe Islands operate under Denmark's AML and TF regulations, ensuring robust risk mitigation.

4.7.3 Svalbard and Jan Mayen

These territories, under Norwegian jurisdiction, are sparsely populated and have minimal economic activity. They lack significant financial systems or international banking infrastructure, greatly reducing their susceptibility to ML or TF activities. Norway's AML/TF standards further bolster the assessment of low risk for these territories.

4.7.4 Åland Islands

The Åland Islands, an autonomous region of Finland, operate under Finnish law, which is well-aligned with European Union AML and TF directives. The region's economy is primarily local and tourism-driven, with limited exposure to high-risk financial activities. This regulatory and economic context supports a low-risk assessment.

4.8 Manual Overrides Sanctions

4.8.1 Norway

Norway was initially classified as medium risk in the model, primarily due to its northern border with Russia, a country subject to extensive international sanctions. However, this elevated risk level does not accurately reflect Norway's overall risk profile.

Norway maintains a low (good) FSI score, indicating strong institutional stability. Furthermore, the country demonstrates relatively limited trade activity with sanctioned jurisdictions. As of May 29, 2025, Norway has fully closed its border with Russia, eliminating the primary geographic exposure that influenced the original classification.

Considering these factors, low FSI score, minimal sanctioned trade exposure, and the closure of the Russian border, the sanction risk classification for Norway is revised from medium to low.

4.8.2 South Korea

South Korea was initially classified as high risk in the model, largely due to its shared border with North Korea, a country under extensive international sanctions. However, this geographic risk is mitigated by the fact that the border is entirely closed and strictly controlled, with no official trade or movement allowed between the two countries. The Demilitarized Zone (DMZ) is one of the most heavily guarded borders in the world, significantly reducing the likelihood of sanction-related exposure via geographic proximity.

While South Korea does engage in some trade with sanctioned jurisdictions, this is conducted under a regulatory environment that includes strong compliance controls, a well-developed financial system, and a low FSI score, reflecting high institutional resilience.

Considering the secure and inactive nature of the North Korea border, the sanction risk classification is revised from high to medium. This adjustment better reflects the actual risk profile.

4.8.3 Svalbard and Jan Mayen

These territories, under Norwegian jurisdiction, have been estimated as medium risk by the model due to lack of data for both trade and FSI, however they are sparsely populated and have minimal economic activity. They lack significant financial systems or international banking infrastructure, greatly reducing their susceptibility to sanction circumvention activities.

4.8.4 Åland Islands

The Åland Islands, an autonomous region of Finland, have been classified based solely on data limitations, particularly the absence of available information regarding trade activity and FSI scoring. This lack of data is the primary factor driving the current classification.

While Finland as a whole is classified as medium risk, primarily due to its extensive land border with Russia—a heavily sanctioned jurisdiction, this geopolitical risk does not entirely translate to the Åland Islands. Åland has no land border with Russia, and its geographic location in the Baltic Sea insulates it from the direct exposure that influences Finland's broader risk profile.

Given the absence of a Russian border and the lack of any clear indicators of significant sanctioned trade activity specific to Åland, the application of Finland's medium-risk rating may overstate the region's actual sanction exposure. As such, the risk will be revised from medium to low for Åland.

4.9 Model output

The country's total risk score is determined by aggregating values from each source, in conjunction with the established thresholds and hard rules. Hard rules, or "dominant" factors, are criteria that override other scores; for example, even if a country has a low-risk value across all sources, it will still be assessed as high risk if it appears on a hard rule list.

It is important to note that the distribution of risk classifications is not intended to follow a normal distribution. Instead, it is derived from external sources that identify countries as high risk. Very high-risk countries are those that appear on "hard rule" lists, such as the FATF (Financial Action Task Force) list, the EUHR3C (European Union High-Risk Third Countries) list, or EU Sanctions Map. This distribution analysis was performed on 2025-10-20 and is regularly updated, at least annually. The follow-up on the model and model documentation is further detailed in section 6.2. I.e., this table is static for a period, while the live distribution may deviate from this document for a set period.

The latest testing was performed 2025-11-20.

Measure	ML	TF	Sanctions
Low	25	38	54
Medium	39	44	112
High	154	136	49

Very high	32	32	35
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4.10 Data quality

4.11 Data quality controls

To ensure high-quality input data, a combination of automated and manual data quality controls has been established. These controls ensure high quality input and output.

After the testing, the data undergoes detailed mathematical analysis using sophisticated statistical methods. These analyses are designed to interpret the data, identify irregularities, and uncover any unusual patterns. The results are reviewed periodically to ensure that they continue to meet the model’s standards.

If any discrepancies or unexpected results are identified, the system automatically triggers an alert. Notifications are sent to both the model developer and product owner, ensuring data potential data quality errors are handled swiftly.

Lastly, since sources often provide information using different naming conventions—such as Russia, Ryssland, Russia*, or the Russian Federation—the model needs to recognize and adapt to these variations. To handle this, a “new” format control has been set up to identify any unfamiliar formats that can’t be directly linked to a specific country. If a match can’t be made, the system flags it and notifies the model developer to map the new format to the correct country. This ensures the model stays accurate and up to date as new variations arise.

4.12 Data testing ML / TF

The model has implemented manual and automatic data quality controls. In addition to this, during model development and follow-up data testing on a sample basis is performed to ensure that input data in the model is equal to the values of source data. In the table below a sub sample of countries was included in the manual test, to ensure that raw source data is equal to model input data, which entails that the gathering process of information is adequate and works as intended.

The latest sample testing was performed 2024-12-17.

Country	Source value	Model value	Assessment
Afghanistan	AML Basel Index: Missing Corruption Perception Index: 20 EU/EES Member: FALSE EUHR3C: TRUE FATF B&G: FALSE FATF Member: FALSE Freedom House Score: 6 Financial Secrecy Index: Missing Global Peace Index: 3.294 Global Terrorism Index: 7.825 Open Budget Transparency: 0.0 EU Tax Haven: 4	AML Basel Index: Missing Corruption Perception Index: 20 EU/EES Member: FALSE EUHR3C: TRUE FATF B&G: FALSE FATF Member: FALSE Freedom House Score: 6 Financial Secrecy Index: Missing Global Peace Index: 3.294 Global Terrorism Index: 7.825 Open Budget Transparency: 0.0 EU Tax Haven: 4	OK

	EU Sanction: 1	EU Sanction: 1	
Sweden	AML Basel Index: 3.45 Corruption Perception Index: 82 EU/EES Member: True EUHR3C: False FATF B&G: Missing FATF Member: True Freedom House Score: 99 Financial Secrecy Index: 44.625 Global Peace Index: 1.782 Global Terrorism Index: 0.735 Open Budget Transparency: 85 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.45 Corruption Perception Index: 82 EU/EES Member: True EUHR3C: False FATF B&G: Missing FATF Member: True Freedom House Score: 99 Financial Secrecy Index: 44.625 Global Peace Index: 1.782 Global Terrorism Index: 0.735 Open Budget Transparency: 85 EU Tax Haven: 1 EU Sanction: 0	OK
Norway	AML Basel Index: 3.76 Corruption Perception Index: 84 EU/EES Member: False EUHR3C: False FATF B&G: Missing FATF Member: True Freedom House Score: 98 Financial Secrecy Index: 53.3 Global Peace Index: 1.638 Global Terrorism Index: 1.747 Open Budget Transparency: 80 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.76 Corruption Perception Index: 84 EU/EES Member: False EUHR3C: False FATF B&G: Missing FATF Member: True Freedom House Score: 98 Financial Secrecy Index: 53.3 Global Peace Index: 1.638 Global Terrorism Index: 1.747 Open Budget Transparency: 80 EU Tax Haven: 1 EU Sanction: 0	OK
Iran	AML Basel Index: missing Corruption Perception Index: 24 EU/EES Member: False EUHR3C: True FATF B&G: Black FATF Member: False Freedom House Score: 11 Financial Secrecy Index: missing Global Peace Index: 2.682 Global Terrorism Index: 4.464 Open Budget Transparency: missing EU Tax Haven: 4 EU Sanction: 1	AML Basel Index: Missing Corruption Perception Index: 24 EU/EES Member: False EUHR3C: True FATF B&G: Black FATF Member: False Freedom House Score: 11 Financial Secrecy Index: missing Global Peace Index: 2.682 Global Terrorism Index: 4.464 Open Budget Transparency: missing EU Tax Haven: 4 EU Sanction: 1	OK

Ireland	AML Basel Index:4.23 Corruption Perception Index: 77 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 47.2 Global Peace Index: 1.303 Global Terrorism Index: 0.03 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.23 Corruption Perception Index: 77 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 47.2 Global Peace Index: 1.303 Global Terrorism Index: 0.03 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Finland	AML Basel Index: 3.07 Corruption Perception Index: 87 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 100 Financial Secrecy Index: 51.8 Global Peace Index: 1.474 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.07 Corruption Perception Index: 87 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 100 Financial Secrecy Index: 51.8 Global Peace Index: 1.474 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Poland	AML Basel Index: 4.34 Corruption Perception Index: 54 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: false Freedom House Score: 80 Financial Secrecy Index: 46.05 Global Peace Index: 1.678 Global Terrorism Index: 0 Open Budget Transparency: 59 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.34 Corruption Perception Index: 54 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: false Freedom House Score: 80 Financial Secrecy Index: 46.05 Global Peace Index: 1.678 Global Terrorism Index: 0 Open Budget Transparency: 59 EU Tax Haven: 1 EU Sanction: 0	OK
France	AML Basel Index: 3.86	AML Basel Index: 3.86	OK

	Corruption Perception Index: 71 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 89 Financial Secrecy Index: 47.875 Global Peace Index: 2.088 Global Terrorism Index: 2.647 Open Budget Transparency: 74 EU Tax Haven: 1 EU Sanction: 0	Corruption Perception Index: 71 EU/EES Member: true EUHR3C: false FATF B&G: missing FATF Member: true Freedom House Score: 89 Financial Secrecy Index: 47.875 Global Peace Index: 2.088 Global Terrorism Index: 2.647 Open Budget Transparency: 74 EU Tax Haven: 1 EU Sanction: 0	
Belarus	AML Basel Index: 5.67 Corruption Perception Index: 37 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 8 Financial Secrecy Index: missing Global Peace Index: 2.291 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 4 EU Sanction: 1	AML Basel Index: 5.67 Corruption Perception Index: 37 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 8 Financial Secrecy Index: missing Global Peace Index: 2.291 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 4 EU Sanction: 1	OK
Germany	AML Basel Index: 4.63 Corruption Perception Index: 78 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 93 Financial Secrecy Index: 56.7 Global Peace Index: 1.542 Global Terrorism Index: 2.782 Open Budget Transparency: 76 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.63 Corruption Perception Index: 78 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 93 Financial Secrecy Index: 56.7 Global Peace Index: 1.542 Global Terrorism Index: 2.782 Open Budget Transparency: 76 EU Tax Haven: 1 EU Sanction: 0	OK
Spain	AML Basel Index: 4.29 Corruption Perception Index: 60	AML Basel Index: 4.29 Corruption Perception Index: 60	OK

	EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 90 Financial Secrecy Index: 56.575 Global Peace Index: 1.597 Global Terrorism Index: 1.669 Open Budget Transparency: 54 EU Tax Haven: 1 EU Sanction: 0	EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 90 Financial Secrecy Index: 56.575 Global Peace Index: 1.597 Global Terrorism Index: 1.669 Open Budget Transparency: 54 EU Tax Haven: 1 EU Sanction: 0	
Estonia	AML Basel Index: 3.16 Corruption Perception Index: 76 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 95 Financial Secrecy Index: 44.2 Global Peace Index: 1.615 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.16 Corruption Perception Index: 76 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 95 Financial Secrecy Index: 44.2 Global Peace Index: 1.615 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Faroe Islands	AML Basel Index: missing Corruption Perception Index: missing EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: missing Financial Secrecy Index: missing Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: missing Corruption Perception Index: missing EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: missing Financial Secrecy Index: missing Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Greenland	AML Basel Index: missing Corruption Perception Index: missing EU/EES Member: false	AML Basel Index: missing Corruption Perception Index: missing EU/EES Member: false	OK

	EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: missing Financial Secrecy Index: missing Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: missing Financial Secrecy Index: missing Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	
Lithuania	AML Basel Index: 3.54 Corruption Perception Index: 61 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 89 Financial Secrecy Index: 50.95 Global Peace Index: 1.672 Global Terrorism Index: 0.059 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.54 Corruption Perception Index: 61 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 89 Financial Secrecy Index: 50.95 Global Peace Index: 1.672 Global Terrorism Index: 0.059 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Latvia	AML Basel Index: 4.08 Corruption Perception Index: 60 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 88 Financial Secrecy Index: 55.275 Global Peace Index: 1.661 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.08 Corruption Perception Index: 60 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 88 Financial Secrecy Index: 55.275 Global Peace Index: 1.661 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Netherlands	AML Basel Index: 4.52 Corruption Perception Index: 79 EU/EES Member: true EUHR3C: false	AML Basel Index: 4.52 Corruption Perception Index: 79 EU/EES Member: true EUHR3C: false	OK

	FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 64.625 Global Peace Index: 1.527 Global Terrorism Index: 0.577 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 64.625 Global Peace Index: 1.527 Global Terrorism Index: 0.577 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	
Denmark	AML Basel Index: 3.5 Corruption Perception Index: 90 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 48.95 Global Peace Index: 1.382 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.5 Corruption Perception Index: 90 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 48.95 Global Peace Index: 1.382 Global Terrorism Index: 0 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Belgium	AML Basel Index: 4.48 Corruption Perception Index: 73 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 52.525 Global Peace Index: 1.51 Global Terrorism Index: 1.904 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.48 Corruption Perception Index: 73 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 52.525 Global Peace Index: 1.51 Global Terrorism Index: 1.904 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Bulgaria	AML Basel Index: 4.99 Corruption Perception Index: 45 EU/EES Member: true EUHR3C: false FATF B&G: grey	AML Basel Index: 4.99 Corruption Perception Index: 45 EU/EES Member: true EUHR3C: false FATF B&G: grey	OK

	FATF Member: false Freedom House Score: 78 Financial Secrecy Index: 52.775 Global Peace Index: 1.629 Global Terrorism Index: 0 Open Budget Transparency: 79 EU Tax Haven: 1 EU Sanction: 0	FATF Member: false Freedom House Score: 78 Financial Secrecy Index: 52.775 Global Peace Index: 1.629 Global Terrorism Index: 0 Open Budget Transparency: 79 EU Tax Haven: 1 EU Sanction: 0	
Cyprus	AML Basel Index: 4.81 Corruption Perception Index: 53 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 92 Financial Secrecy Index: 61.525 Global Peace Index: 2.026 Global Terrorism Index: 0.616 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.81 Corruption Perception Index: 53 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 92 Financial Secrecy Index: 61.525 Global Peace Index: 2.026 Global Terrorism Index: 0.616 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
The Czech Republic/ Czechia	AML Basel Index: 3.85 Corruption Perception Index: 57 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 94 Financial Secrecy Index: 50 Global Peace Index: 1.459 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.85 Corruption Perception Index: 57 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 94 Financial Secrecy Index: 50 Global Peace Index: 1.459 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	OK
Greece	AML Basel Index: 3.66 Corruption Perception Index: 49 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true	AML Basel Index: 3.66 Corruption Perception Index: 49 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true	OK

	Freedom House Score: 85 Financial Secrecy Index: 52.825 Global Peace Index: 1.793 Global Terrorism Index: 3.028 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	Freedom House Score: 85 Financial Secrecy Index: 52.825 Global Peace Index: 1.793 Global Terrorism Index: 3.028 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	
Hungary	AML Basel Index: 5.06 Corruption Perception Index: 42 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 65 Financial Secrecy Index: 55.2 Global Peace Index: 1.502 Global Terrorism Index: 0 Open Budget Transparency: 22 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 5.06 Corruption Perception Index: 42 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 65 Financial Secrecy Index: 55.2 Global Peace Index: 1.502 Global Terrorism Index: 0 Open Budget Transparency: 22 EU Tax Haven: 1 EU Sanction: 0	OK
Luxemburg	AML Basel Index: 3.99 Corruption Perception Index: 78 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 54.975 Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.99 Corruption Perception Index: 78 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 97 Financial Secrecy Index: 54.975 Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Romania	AML Basel Index: 4.99 Corruption Perception Index: 46 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 83	AML Basel Index: 4.99 Corruption Perception Index: 46 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 83	OK

	Financial Secrecy Index: 59.375 Global Peace Index: 1.755 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	Financial Secrecy Index: 59.375 Global Peace Index: 1.755 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	
Slovakia	AML Basel Index: 4.39 Corruption Perception Index: 54 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 90 Financial Secrecy Index: 53.175 Global Peace Index: 1.634 Global Terrorism Index: 1.092 Open Budget Transparency: 69 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.39 Corruption Perception Index: 54 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 90 Financial Secrecy Index: 53.175 Global Peace Index: 1.634 Global Terrorism Index: 1.092 Open Budget Transparency: 69 EU Tax Haven: 1 EU Sanction: 0	OK
Slovenia	AML Basel Index: 3.54 Corruption Perception Index: 56 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 96 Financial Secrecy Index: 35.875 Global Peace Index: 1.395 Global Terrorism Index: 0 Open Budget Transparency: 64 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3.54 Corruption Perception Index: 56 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 96 Financial Secrecy Index: 35.875 Global Peace Index: 1.395 Global Terrorism Index: 0 Open Budget Transparency: 64 EU Tax Haven: 1 EU Sanction: 0	OK
Malta	AML Basel Index: 5.18 Corruption Perception Index: 51 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 87 Financial Secrecy Index: 53.925	AML Basel Index: 5.18 Corruption Perception Index: 51 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: false Freedom House Score: 87 Financial Secrecy Index: 53.925	OK

	Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	Global Peace Index: missing Global Terrorism Index: missing Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	
United Kingdom	AML Basel Index: 4.14 Corruption Perception Index: 71 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 91 Financial Secrecy Index: 47.175 Global Peace Index: 1.703 Global Terrorism Index: 2.373 Open Budget Transparency: 62 EU Tax Haven: 4 EU Sanction: 0	AML Basel Index: 4.14 Corruption Perception Index: 71 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 91 Financial Secrecy Index: 47.175 Global Peace Index: 1.703 Global Terrorism Index: 2.373 Open Budget Transparency: 62 EU Tax Haven: 4 EU Sanction: 0	OK
Austria	AML Basel Index: 4.35 Corruption Perception Index: 71 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 93 Financial Secrecy Index: 54.625 Global Peace Index: 1.313 Global Terrorism Index: 0.953 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.35 Corruption Perception Index: 71 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 93 Financial Secrecy Index: 54.625 Global Peace Index: 1.313 Global Terrorism Index: 0.953 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Switzerland	AML Basel Index: 4.46 Corruption Perception Index: 82 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 70.05 Global Peace Index: 1.35	AML Basel Index: 4.46 Corruption Perception Index: 82 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 70.05 Global Peace Index: 1.35	OK

	Global Terrorism Index: 0.627 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	Global Terrorism Index: 0.627 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	
Iceland	AML Basel Index: 3 Corruption Perception Index: 72 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 94 Financial Secrecy Index: 42.45 Global Peace Index: 1.112 Global Terrorism Index: 0.233 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 3 Corruption Perception Index: 72 EU/EES Member: false EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 94 Financial Secrecy Index: 42.45 Global Peace Index: 1.112 Global Terrorism Index: 0.233 Open Budget Transparency: missing EU Tax Haven: 1 EU Sanction: 0	OK
Portugal	AML Basel Index: 4.09 Corruption Perception Index: 61 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 56.875 Global Peace Index: 1.372 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	AML Basel Index: 4.09 Corruption Perception Index: 61 EU/EES Member: true EUHR3C: false FATF B&G: false FATF Member: true Freedom House Score: 96 Financial Secrecy Index: 56.875 Global Peace Index: 1.372 Global Terrorism Index: 0 Open Budget Transparency: 62 EU Tax Haven: 1 EU Sanction: 0	OK

4.13 Data testing Sanctions

Data quality controls for sanctions slightly differs compared to ML/TF, due to the input variables being function of sanctions. However, data quality controls have still been performed.

Sanction score: in the model, 32 countries have a sanction score, when analyzing EU sanction map it's noted that 35 countries have 1 or more restrictive measures. However, 3 have been excluded from the model, Serbia, US and Montenegro due to no active restrictive measures.

In the model input North Korea, Russia, Belarus, Syria and Ukraine have the most active restrictive measures, while China, Turkey, Tunisia have the fewest, this is in line with a manual control performed on 2025-05-30 directly on

the EU website.

FSI: The FSI score is tested via the ML/TF data quality controls and is not required to test again for the sanction score, i.e., it's the same variable.

Trade: North Korea, Armenia and Mongolia have the highest trade score (i.e., trade with sanctioned party) while Bonaire Sint Eustatius Saba, Saint Pierre and Miquelon, Anguilla have the lowest trade score. Cross checking this model input with data from CEEPI it's noted that the first 3 countries have a very high trade percentage towards sanctioned jurisdictions while the lowest 3 has next to none, implying that the model input is aligned with raw data from source.

Country	Largest export to	Largest import from	Value in model - Assessment
ARM	RUS ARE HKG	RUS CHN VNM	0,8901 (high)
KGZ	CHN RUS ARE	CHE RUS KAZ	0,7308 (high)
RUS	CHN IND TUR	CHN TUR KAZ	0,5698 (high)

4.14 Data flow

The model data flow is designed to be efficient and streamlined, involving two key data points: source data and model data.

- **Data Collection:** The process begins with raw data collection from various external sources. This collected data is then organized and stored in an SQL database for subsequent processing.
- **Data Processing:** The core of the model's functionality relies on Python to execute various analytical and computational tasks. These Python-based operations process the source data, applying the necessary algorithms and transformations to generate model data.
- **Data Storage:** Both the source data and the results of the model executions are stored in SQL databases. This storage solution ensures that the data is organized, secure, and readily accessible for future reference or analysis.

Overall, this simple yet effective data flow ensures that data is efficiently captured, processed, and stored, facilitating smooth operations and reliable outputs from the model.

5 Framework

5.1.1 System configuration

The country risk assessment is stored and calculated in an SQL database, with data being retrieved daily from the sources listed in section 2.3. The calculations are performed daily to estimate the risk assessment. If a change is detected compared to the previous day's calculation, a notification is sent to the model developer to verify the accuracy of the risk change. Additionally, the client will be informed that a new country risk assessment is available.

5.1.2 Follow-up

To ensure the model functions as intended, it is essential to conduct periodic follow-ups and evaluations. Each follow-up will include an analysis of the following aspects:

- **Changes in Risk Classification:** The number of countries that have experienced a change in risk classification during the recent period
- **Country Inclusion Analysis:** The comparison of the number of countries included at the beginning of the period versus those included at the end of the period
- **Risk Classification Distribution:** The distribution of countries across different risk classifications

If any of these key aspects deviate from expectations, further analysis will be required to determine whether the model remains fit-for-purpose or if adjustments—minor or major—are necessary. Follow-ups should be conducted annually, or sooner if significant changes are made to the model, such as the addition of risk factors or modifications to the underlying model logic. This ensures the model continues to perform accurately and effectively in line with its objectives.

5.1.3 Distribution of model output

While the distribution of the list is not directly part of the model itself, it plays a crucial role in the overall process and the delivery of results. To maintain the integrity of the final output, a manual review is conducted before the list is transmitted to the client. This step ensures that the results align with expectations and expert opinions, providing an additional layer of validation and quality control to guarantee the reliability of the information shared with the client.

5.1.4 Validation

The model has been validated in accordance with Frank Penny's framework for model validation. However, certain limitations regarding model validation have been identified, as previously noted. Any processes related to the implementation of the list on the client side are outside the scope of Frank Penny's validation and have therefore not been evaluated. The model validation performed by Frank Penny does not necessarily replace the requirement of a model validation by the client, since the routines and guidelines for model validation may differ.

Therefore, each client has to assess whether this is classified as a model and therefore determine whether it has to be validated or not in accordance with internal validation guidelines.

5.1.5 Model changes

Changes to the model may be implemented either during scheduled follow-ups or as needed. Any modifications affecting the model's logic or output must be communicated to all relevant parties. Additionally, significant changes will require model validation, which may be either full or limited validation, to ensure that the adjustments uphold the model's integrity and objectives.

Major changes involve fundamental alterations to how the model operates and require the same level of testing and analysis performed during the model development process. Examples of major changes include:

- Change in the model design, from a weighted additive model to an AI-model
- Changes to the model's objective
- Changes in the underlying systematic logic, i.e., the calculations are entirely moved from one system to another

As previously noted, all major changes must be documented. If they impact model output or logic, the adjustments must be communicated to relevant parties.

6 Appendices

6.1.1 Country risk calculations

Following are the formulas for the sources:

$$FATFMember_i = AdjustedWeight_{FATFMember} * FATFMember(0) + 0 * FATFMember(1),$$

where $FATFMember(0) = 1$ and $FATFMember(1) = 0$

$$EUMember_i = AdjustedWeight_{EUMember} * EUMember(0) + 0 * EUMember(1)$$

where $EUMember(0) = 1$ and $EUMember(1) = 0$

FSI Score if NULL:

$$FSIScore = \frac{Third\ Quartile_{FSIScore} - Min_{FSIScore}}{Max_{FSIScore} - Min_{FSIScore}} * AdjustedWeight_{FSIScore}$$

FSI Score if not NULL:

$$FSIScore_i = \frac{FSIValue_i - Min_{FSIScore}}{Max_{FSIScore} - Min_{FSIScore}} * AdjustedWeight_{FSIScore}$$

CPI Score if NULL:

$$CPIScore = \frac{1 - Third\ Quartile_{FSIScore} - Min_{CPIScore}}{Max_{CPIScore} - Min_{CPIScore}} * AdjustedWeight_{CPIScore}$$

CPI Score if not NULL:

$$CPIScore = \frac{1 - CPIValue_i - Min_{CPIScore}}{Max_{CPIScore} - Min_{CPIScore}} * AdjustedWeight_{CPIScore}$$

FreedomHouse Score if NULL:

$$\begin{aligned} & \text{FreedomHouse Score} \\ &= \frac{1 - Third\ Quartile_{FreedomHouseScore} - Min_{FreedomHouseScore}}{Max_{FreedomHouseScore} - Min_{FreedomHouseScore}} \\ & * AdjustedWeight_{FreedomHouseScore} \end{aligned}$$

FreedomHouse Score if not NULL:

$$\begin{aligned} & \text{FreedomHouseScore}_i \text{ FreedomHouse Score} \\ &= \frac{1 - FreedomHouseScore_i - Min_{FreedomHouseScore}}{Max_{FreedomHouseScore} - Min_{FreedomHouseScore}} * AdjustedWeight_{FreedomHouseScore} \end{aligned}$$

Open Budget Transparency if NULL:

$$\begin{aligned} & \text{OpenBudgetTransparencyScore} \\ &= \frac{1 - \text{Third Quartile}_{\text{OpenBudgetTransparencyScore}} - \text{Min}_{\text{OpenBudgetTransparencyScore}}}{\text{Max}_{\text{OpenBudgetTransparencyScore}} - \text{Min}_{\text{OpenBudgetTransparencyScore}}} \\ & \quad * \text{AdjustedWeight}_{\text{OpenBudgetTransparencyScore}} \end{aligned}$$

Open Budget Transparency if not NULL:

$$\begin{aligned} & \text{OpenBudgetTransparencyScore} \\ &= \frac{1 - \text{OpenBudgetTransparencyScore}_i - \text{Min}_{\text{OpenBudgetTransparencyScore}}}{\text{Max}_{\text{OpenBudgetTransparencyScore}} - \text{Min}_{\text{OpenBudgetTransparencyScore}}} \\ & \quad * \text{AdjustedWeight}_{\text{OpenBudgetTransparencyScore}} \end{aligned}$$

GPI Score if NULL:

$$\text{GPIScore} = \frac{\text{Third Quartile}_{\text{GPIScore}} - \text{Min}_{\text{GPIScore}}}{\text{Max}_{\text{GPIScore}} - \text{Min}_{\text{GPIScore}}} * \text{AdjustedWeight}_{\text{GPIScore}}$$

GPI Score if not NULL:

$$\text{GPIScore}_i = \frac{\text{GPIScore}_i - \text{Min}_{\text{GPIScore}}}{\text{Max}_{\text{GPIScore}} - \text{Min}_{\text{GPIScore}}} * \text{AdjustedWeight}_{\text{GPIScore}}$$

Global Terrorism Index Score if NULL:

$$\begin{aligned} & \text{GlobalTerrorismIndexScore} \\ &= \frac{\text{Third Quartile}_{\text{GlobalTerrorismIndexScore}} - \text{Min}_{\text{GlobalTerrorismIndexScore}}}{\text{Max}_{\text{GlobalTerrorismIndexScore}} - \text{Min}_{\text{GlobalTerrorismIndexScore}}} \\ & \quad * \text{AdjustedWeight}_{\text{GlobalTerrorismIndexScore}} \end{aligned}$$

Global Terrorism Index Score if not NULL:

$$\begin{aligned} & \text{GlobalTerrorismIndexScore}_i \\ &= \frac{\text{GlobalTerrorismIndexScore}_i - \text{Min}_{\text{GlobalTerrorismIndexScore}}}{\text{Max}_{\text{GlobalTerrorismIndexScore}} - \text{Min}_{\text{GlobalTerrorismIndexScore}}} \\ & \quad * \text{AdjustedWeight}_{\text{GlobalTerrorismIndexScore}} \end{aligned}$$

Basel AML Index Score if NULL:

$$\begin{aligned} & \text{BaselAMLIndexScore} \\ &= \frac{\text{Third Quartile}_{\text{BaselAMLIndexScore}} - \text{Min}_{\text{BaselAMLIndexScore}}}{\text{Max}_{\text{BaselAMLIndexScore}} - \text{Min}_{\text{BaselAMLIndexScore}}} \\ & \quad * \text{AdjustedWeight}_{\text{BaselAMLIndexScore}} \end{aligned}$$

Basel AML Index Score if not NULL:

$$\begin{aligned} & \text{BaselAMLIndexScore}_i \\ &= \frac{\text{BaselAMLIndexScore}_i - \text{Min}_{\text{BaselAMLIndexScore}}}{\text{Max}_{\text{BaselAMLIndexScore}} - \text{Min}_{\text{BaselAMLIndexScore}}} * \text{AdjustedWeight}_{\text{BaselAMLIndexScore}} \end{aligned}$$

6.1.2 Completeness analysis – Missing values

Country

Åland Islands
 Antarctica
 Bonaire Sint Eustatius Saba
 Bouvet Island
 British Indian Ocean Territory
 Christmas Island
 The Cocos Islands
 The Falkland Islands
 The Faroe Islands
 French Guiana
 French Polynesia
 French Southern Territories
 Greenland
 Guadeloupe
 Heard Island and McDonald Islands
 Holy See
 Martinique
 Mayotte
 New Caledonia
 Niue
 Norfolk Island
 Northern Mariana Islands
 Pitcairn
 Réunion
 Saint Barthélemy
 Saint Helena Ascension Island Tristan da Cunha
 Saint Martin
 Saint Pierre and Miquelon
 Sint Maarten
 South Georgia and the South Sandwich Islands
 Svalbard Jan Mayen
 Tokelau
 United States Minor Outlying Islands
 Vatican City
 Virgin Islands
 Wallis and Futuna
 Western Sahara

6.1.3 EU Sanctions Coverage analysis

Country	EU Sanction Map	FINCen311	OFAC	HM Treasury

Afghanistan	X		X	X
Belarus	X		X	X
Bosnia & Herzegovina	X			X
Central African Republic	X		X	X
China	X			
Democratic People's Republic of Korea (DPRK – North Korea)	X		X	X
Democratic Republic of the Congo	X		X	X
Guatemala	X			
Guinea	X			X
Guinea-Bissau	X			X
Haiti	X			X
Iran	X	X	X	X
Iraq	X		X	X
Lebanon	X		X	X
Libya	X		X	X
Mali	X		X	X
Moldova	X			
Montenegro	X			
Myanmar (Burma)	X	X	X	X
Nicaragua	X		X	X
Niger	X			
Russia	X		X	X
Serbia	X			
Somalia	X		X	X

South Sudan	X		X	X
Sudan	X		X	X
Syria	X		X	X
Tunisia	X			
Türkiye	X			
Ukraine	X	X		
United States	X			
Venezuela	X		X	X
Yemen	X		X	X
Zimbabwe	X			X
Nauru		X		
Cuba			X	
Ethiopia			X	
Hong Kong			X	