

**SPIS RISK INDICATORS**

**METHODOLOGY GUIDE**

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## 1 Introduction

Following SPIS decision to require each member to calculate risk indicators for its structured products, there is a need to set the detailed rules of the methodology, in order to ensure consistency of the calculations between the members.

This guide details the specific rules of the risk indicators calculation methodology. It begins with describing the two risk indicators, continues with listing the assumptions and logic of the Monte Carlo mechanism, and then covers market data issues.

## 2 Risk Indicators

### 2.1 Indicator #1: VaR 99%

This risk indicator denotes the maximal potential loss at maturity in 99% level of confidence as calculated by the Monte Carlo (MC) engine (see relevant section below). After the calculation, the result is normalized to a 1 to 7 scale for simplicity and ease of comparison.

#### 2.1.1 Calculation Methodology

1. A MC engine generates prices for each one of the product's underlyers for a pre-defined number of simulations under a set of assumptions - see section 3 for the Monte Carlo parameters.
2. The product's payoff/return is calculated per each of the above simulations.
3. The returns are then ordered in an ascending order from the worst to the best.
4. The return at the 1<sup>st</sup> percentile is the return that indicates the VaR 99%. One can say that with 99% confidence, the product is not expected to lose more than the VaR 99% return. Running with 10,000 simulations, the 100<sup>th</sup> worst simulation is the VaR 99%.
5. VaR volatility ( $V$ ) is calculated by inputting the VaR 99% value in the next equation:

$$V = \frac{\sqrt{-LN(1 + VaR) + \frac{Z(p)^2}{2}} + \frac{Z(p)}{\sqrt{2}}}{\sqrt{\frac{T}{2}}} = \frac{\sqrt{-LN(1 + VaR) + \frac{Z(0.99)^2}{2}} + \frac{Z(0.99)}{\sqrt{2}}}{\sqrt{\frac{T}{2}}}$$

$$= \frac{\sqrt{\sim 2.7059 - LN(1 + VaR)} - \sim 1.6449}{\sqrt{\frac{T}{2}}}$$

Where:

$VaR$  = The return that indicates the VaR 99% value.

$T$  = Product maturity in years.

### 2.1.2 Mapping to Risk Scale

In order to be able to easily compare between the wide varieties of products, the VaR volatility is then mapped to a scale of 1 to 7 according to the following table:

Risk Class	Volatility Intervals	
	Equal or above	Less than
1	0%	0.5%
2	0.5%	2%
3	2%	5%
4	5%	10%
5	10%	15%
6	15%	25%
7	25%	

## 2.2 Indicator #2: Average Downside

As opposed to the VaR 99% indicator, the Average Downside indicator supplies information about the volatility of the product, rather than its possible negative return.

Most Structured Products utilize an option component which reflects the product's market risk component. The calculation of the Average Downside indicator is based on the pricing of the option and uncovers the risk it holds.

### 2.2.1 Calculation Methodology

1. A MC engine generates prices for each one of the product's underlyers for a pre-defined number of simulations under a set of assumptions - see section 3 for the Monte Carlo parameters.
2. The product's payoff/return is calculated per each of the above simulations.
3. Positive returns are modified to be equal to 0%. Negative returns keep their value.
4. The absolute value of the average of all returns from the last step is calculated (M).
5. The calculated value of M is then inserted into the Black & Scholes equation as the premium of a put option on the redemption level of the product so that the option's premium equals to the product of M and the strike price.

The risk free rate is omitted from the Black & Scholes equation since this value is the current value and does not refer to the rate that will exist at option's maturity.

For a product with more than 1 underlyer, the strike is expressed in basis points (for example: a strike price of 100 for an "at the money" option).

6. Given the fact that the option's premium is known, and that all the other parameters of the formula are also known parameters (underlyer's price, option's term, etc.), the underlyer's volatility is extracted from the B&S formula.
7. The extracted volatility reflects the value of the Average Downside indicator.

### 2.2.2 Mapping to Risk Scale

The values received from the last step are distributed to volatility intervals that crowd the products in "buckets". The buckets differ between different groups of products that possess different levels of risk. The next table provides volatility intervals which reflect the increasing level of risk borne by the product and, therefore, its position in the risk scale.

Risk Class	Volatility Intervals	
	Equal or above	Less than
1	0%	0.5%
2	0.5%	2%
3	2%	5%
4	5%	10%
5	10%	15%
6	15%	25%
7	25%	

## 3 Monte Carlo Engine

The MC engine is the component that is responsible for the generation of price simulations; these prices are then taken as input to the model that calculates the product's return.

The generation of prices is performed by applying the following steps:

1. Generate a normally distributed random number for each day of the product's term, and for each underlying. Output produces a vector of T values for each one of the product's underlyers (where T equals the number of days since product's issue date until its maturity).
2. Calculate the correlation matrix ( $C$ ) for the product's underlyers. The calculation is described in paragraph 3.6 since the matrix is actually an input for the engine.
3. Generate a correlation decomposition matrix ( $U$ ) for the correlation matrix product's underlyers ( $C$ ).

Correlation decomposition matrix is calculated by one of these methods:

- Cholesky Decomposition.
  - Spectral Decomposition. The Cholesky Decomposition fails when the determinant of the correlation matrix equals to 0. In that case the Spectral Decomposition is applied although it's more complicated and takes longer to compute.
4. For each day, multiply the random numbers generated in step 1 with the correlation decomposition matrix generated in step 3. This results in a vector of T values for each

one of the product's underlyers; the values are normally distributed but as opposed to the vector that was created in step 1, the values are also correlated.

5. Generate prices for each one of the underlyers using the next formula:

$$P(t_i) = P(t_{i-1}) \times e^{\left(\mu - \frac{\sigma^2}{2}\right) \times \Delta t + \sigma \times N(0,1) \times \sqrt{\Delta t}}$$

Where:

- $i = 1, \dots, N$ ,  $t_N$  is the Maturity Date of the product.
- $P(t_0)$  is the price of underlyer on the first day
- $\Delta t$  = time interval between two series points  
If the time interval is **daily**:  $\Delta t = 1/365$   
If the time interval is **weekly**:  $\Delta t = 7/365$
- $\mu$  = Expected Return, see calculation method in paragraph 3.2.
- $\sigma$  = Expected Volatility, see calculation method in paragraph 3.5.
- $N(0,1)$  = The relevant random number that was generated in step 5 (or in step 1 in cases where the product contains only one underlyer).

6. Once all relevant prices are generated, the calculation model steps in and calculates the product's return based on its payoff and as derived from the prices.

These above steps are conducted per each simulation. The complete set of parameters for the MC mechanism follows.

### 3.1 Number of Simulations

The MC engine can generate a variable amount of simulations where each simulation contains a set of prices for each of the product's underlyers. To ensure the MC consistency, the minimal number of simulations should be 10,000.

### 3.2 Expected Returns

The MC engine receives as parameters an expected return value for each of the product's relevant underlying instruments. The calculation of the Expected Returns (ER) will be performed as follows:

A set of Reference Indices (RI) will be defined (such as: OMX30, Stoxx50, S&P500, etc.).

The Expected Return of each of the Reference Entities will be performed as follows:

- **Equity Risk Premium (ERP)** = Dividend Yield + Real Growth – Real Long Term Yield  
= Dividend Yield + Real Growth + Long Term Inflation – Nominal Long Term Yield
- **Expected Nominal Total Return** = Nominal Long Term Yield + ERP = Dividend Yield + Real Growth + Long Term Inflation Rate
- **Expected Return** = **Expected Nominal Total Return – Dividend Yield**

Where:

- **Real Growth**: is a fixed constant that is commonly between 1.0-1.5%. In these calculations, we will use the fixed value 1.25%.

- **Nominal Long Term Yield:** We will use the 10Y Semi Annual Swap Rate on the relevant currency (see Drift Parameters). If the exact swap can't be found, a similar one will be selected. Example of relevant Bloomberg tickers for various currencies: "USSW10 BGN Curncy", "SKSW10 Curncy", "EUSA10"
- **Long Term Inflation Rate:** A 10Y Zero Coupon Inflation Rate on the relevant currency (see drift parameters). Example of relevant Bloomberg tickers for various currencies: "USSWIT10 Curncy", "EUSWIT10"
- **Dividend Yield:** see Dividends section below.

For each underlying instrument, which is not a Reference Index:

- Assign a Reference Index to the instrument.
- Using the standard Capital Asset Pricing Model (CAPM), calculate the Expected Nominal Total Return of the instrument:

$$ENTR = R_f + \beta * [ER(RI) - R_f]$$

$$ER = ENTR - DIV$$

Where:

- **ENTR:** Expected Nominal Total Return of the instrument
- **R<sub>f</sub>:** Nominal Long Term Yield (see above)
- **ER(RI):** Expected Nominal Total Return of the Reference Index (see above)
- **ER:** Expected Return of the instrument
- **DIV:** Dividend Yield of the instrument

**Note:**

Since in many cases the risk premium, dividend yield and currency discount rate, almost cancel each other and for simplicity of calculation, the expected return will be set as **zero (0%)**.

### 3.3 Drift parameters

The currency for a SEK product with quanto (i.e. the underlying price is handled as it is quoted in SEK and not converted using the FX rate) should be the underlying's denominated currency. For example: For a quanto product that uses the FTSE 100 index as an underlyer the GBP swap rate should be used. In case of a SEK denominated underlying, the SEK swap rate should be used.

For a non quanto SEK product (where the underlying price is converted from its denominated currency to SEK), the SEK swap rate should be used, regardless of its underlyer's currency.

### 3.4 Dividends

Since product holders usually do not enjoy underlyers' dividend payments, the expected dividend rate should be subtracted from the underlyers' return expectations. Dividend

payments should be extracted from a reliable source. For example: Bloomberg's Projected 12M Dividend Yield.

In a few cases the timing of the dividends has a major effect on the calculations and therefore should be taken into account. For example: an Autocall product with quarterly Autocall interval on a share that pays an annual dividend might need to consider the timing of the dividend. For these cases where dividends' timing may have a great influence on the product's payoff, the expected ex dates of the dividends should be extracted from a reliable source, along with the dividend's absolute amounts. For example: Bloomberg's BDVD page (see picture) displays the expected dividends for the next years, each accompanied with its specific ex date. In case product term is longer than available future dividends, last dividend values should be replicated, using the same dividend interval (e.g. annual, quarterly).



Note:

When “synthetic dividends” are used for an underlying (mainly in funds), these should also be reduced from the expected return, in the same manner done for “real dividends”.

### 3.5 Other Costs

When underlyers embed additional fees, for example ETFs, the expected fees should be reduced from the expected return. In the ETF example, the management fee should be reduced.

### 3.6 Expected Volatilities

Volatilities are considered more predictable than returns. Therefore, the usage of past data for the estimation of volatilities is more likely to be effective. The volatility is calculated based on a historical period of 5 years with weekly observations (i.e. 5 year realized volatility).

The calculation steps are as follows:

1. Extract weekly returns based on the prices from the last 5 years at the close of Wednesdays, as it is the weekday with the least holidays and the biggest distance from the weekend. In case events have major effect on the returns, the prices should be adjusted, to prevent an unjustified increase in volatility due to “artificial” price changes.
2. Calculate standard deviation for the natural logarithm of the returns.
3. Multiply the result by  $\sqrt{52}$  to convert the volatility from weekly to annual volatility.

$$Volatility = \sqrt{\frac{52}{T-1} \sum_{t=1}^T (R_w - \overline{R_w})^2}$$

Where:

$T$  = Number of weekly observations

$R_w = \ln(1 + R_t)$

$\overline{R_w}$  = Average of all  $R_w$  Observations

$R_t$  = Weekly return on observation  $t$

### 3.7 Correlations

When a stress test is performed on a product that involves more than a single underlying, correlations become a crucial parameter. Correlations should be calculated based on a historical period of 5 years. The correlations are calculated based on weekly returns of the underlyers, at the close of Wednesdays.

### 3.8 Underlying Instrument Classes and Types

Structured Products utilize a variety of instruments from different asset classes and types. The MC parameters mentioned above are calculated in the same manner for the various types, but it is possible that some instruments may require application of different logic due to their unique and specific nature.

- Equity indices and shares

These types of instruments use the standard inputs for expected return and volatility, as described in paragraphs 3.2 - 3.5.

- Indices and other underlyers with target volatility.  
Their realized volatility should be used (like any other instrument), reflecting the actual effectiveness of the strategy, and also to overcome different volatility measures used across the industry.

## 4 Market Data

### 4.1 Data Sources

Reliable market data is a very important factor when calculating the risk indicators. Discrepancies in data may lead to distorted results that may not reflect the product's risk in the most accurate way. Data sources should be common, reliable sources such as Bloomberg and Reuters.

### 4.2 Handling Data Failures/Challenges

As mentioned earlier in the document, some of the MC engine parameters are calculated based on historical data. The data sometimes contain failures and “noises” that, if not handled correctly, may cause miscalculations of the risk indicators.

#### 4.2.1 Short History

Short history is typically the case for new underlyers. In addition, in a few cases, a major event happened to an instrument, causing the historical prices before the event to be irrelevant. For example, a fund that completely revised its investment policy or a share in a company that completely changed its business. In these circumstances the relevant returns of the instrument are available only from the date of inception of the new investment policy or company business. This time period may fall short of the span of time required for the calculation of expected volatility and correlations (5 years). On the other hand, sometimes the short history is due to technical reasons, i.e. the historical market data resides in other similar instruments, such as different types/series of shares (e.g. common, preferred) of the same company. In these cases, the missing history should be completed with the relevant instrument.

Handling short history should be performed differently if the underlying is a synthetic instrument or a basic instrument. A synthetic instrument is one that is calculated with a formula that depends on other instruments, such as an ETF or a low volatility index. Otherwise, it is considered as a basic instrument, e.g. share, equity index, commodity.

Handling short history of a basic instrument should be carried out as follows:  
If there is at least 1 year of history – use the available history.

If there is less than one year of history, a replacement for missing history should be taken. The replacement should be highly correlated with the original underlying (based on the existing history) and should belong to the same “nature of business”, e.g. industry or sector (in case of shares).

Handling short history of a synthetic instrument should be carried out as follows:

The missing historical prices should be completed by calculating the instrument’s formula. For example, ETF history can be calculated using the tracked index plus its historical distributions (dividends, based on the ETF rules, i.e. if it pays full dividends, or part of them) minus its expenses, i.e. Total Expense Ratio (TER).

#### 4.2.2 Corporate Actions Adjustment

Corporate actions (CA) that are performed on assets may cause price distortions if not handled correctly. CA that cause major changes to prices should be adjusted.

## 5 Credit Linked Notes (CLNs)

As described in previous chapters, when calculating the risk indicators of structured products that belong to asset classes such as equities, FX, interest rates and commodities, the calculation takes into consideration the market risk but not the issuer's credit risk. The credit risk is reflected in the credit rating that is published within each product's documentation.

The reason for not including the issuer's credit risk within those products' risk indicators is related to the fact that usually people invest in those products to benefit from the underlying market and are willing to bear the market risk in return.

In the case of Credit Linked Notes, the client intentionally chooses to get exposed to the credit asset class. The credit is the essence of the product, and as such, it should be treated as the market whose risk should be quantified. To dispel any doubt, the issuer's credit risk is treated in CLNs exactly the same as it is handled in other structured products, i.e. by publishing the issuer's credit rating.

This chapter explains the model to calculate the risk indicators of Credit Linked Notes, which is different from the model used for structured products that belong to asset classes such as equities, FX, interest rates and commodities. The explanation is described bottom up, starting from the building blocks and then describing how to compose them together to handle the different variations of CLNs (Single Name, Basket/Index and Hybrid).

## 5.1 Single Entity Default Probability (DP)

The DP of a reference entity is derived from the entity's credit quality. Therefore, the DP should be calculated based on the credit rating of the specific debt. This should be done using historical statistics on default events per credit rating, provided by a reliable source such as the well-known credit rating agencies.

Since the timing of a credit event affects the payout, it should be taken into consideration, i.e. the default probabilities should be calculated per period, specifically per year as most products pay annual coupons. Therefore, the default probabilities should have two dimensions: credit rating and period.

DPs for year fractions should assume linear defaults along the year, e.g. DP for 6 months equals 50% of the annual DP.

In case a debt (reference entity) is not rated, a different source should be used to estimate the rating in the following order:

- Credit rating of the specific debt by a different agency
- Long term credit rating of the company by any credit rating agency
- (i) Find the entity's CDS spread (ii) look for a rated entity that operates in the same sector and has a similar CDS spread (with the same debt seniority)
- Assign the average DP of the basket of entities (irrelevant in case of a Single Name CLN)

## 5.2 Correlations

When there are multiple reference entities, e.g. in basket/index based CLNs, a correlation model should be applied. The model is based on the Basel II IRB Risk Weight Functions. The correlations were derived by an analysis of data sets from G10 supervisors and are reflected in the following formula:

$$\text{Correlations } (R) = 0.12 \times \left( \frac{1 - e^{-50 \times DP}}{1 - e^{-50}} \right) + 0.24 \times \left( 1 - \frac{1 - e^{-50 \times DP}}{1 - e^{-50}} \right) - 0.04 \times \left( 1 - \frac{S-5}{45} \right)$$

Where:

*DP* = 1-year default probability

*S* = Size adjustment (to be applied for annual sales between 5 mn and 50 mn). For simplicity reasons, in the first phase *S* = 50. i.e. the entire last component is reset to zero)

Further details can be found in “An Explanatory Note on the Basel II IRB Risk Weight Functions”, chapter 5.2 (available at <http://www.bis.org/bcbs/irbriskweight.pdf>), but the above formula is sufficient.

### 5.3 Estimating Defaults in a Basket of Reference Entities

One factor Gaussian copula model is used to compute the distribution of default events. These are the phases of the simulation:

1. Retrieve  $DP_{i,t}$  for each reference entity

Where:

$DP_{i,t}$  = Cumulative expected default rate of reference  $i$  from the beginning of the product's term till year  $t$ .

2. Generate a normal random variable  $X_i$  according to the following formula:

$$X_i = \sqrt{R_i} \times M + \sqrt{1 - R_i} \times Z_i$$

Where:

$R_i$  = Correlation calculated according to section 5.2 above.

$M$  = Standard normal common variable that represents the market

$Z_i$  = Standard normal variable that represents the specific risk of entity  $i$

3. Find if a default event occurred during the product's term. If yes, then find in which year the default occurred.

- Compute  $D_i = \Phi(X_i)$

Where:

$\Phi$  = Standard normal distribution

- If for  $t$  = product's term,  $D_i < DP_{i,t} \rightarrow$  a default event occurred during the product's term

- Find the maximal  $t$  for which  $DP_{i,t-1} < D_i < DP_{i,t}$ . This  $t$  represents the year in which a default event occurred

4. Perform linear interpolation in order to find the time to default.

$$\tau_i = (D_i - DP_{i,t-1}) / (DP_{i,t} - DP_{i,t-1}) + (t-1)$$

### 5.4 Recovery Rates

For products with market recovery (as opposed to zero recovery), an estimation of the recovery rate should be made. The most important factor affecting the recovery rate is the debt seniority, while the industry has much less effect.

For simplicity, the market recovery should be set at 35%, a conservative figure taking into consideration the following:

- Moody's historical statistic of 37.2% average recovery rate between 1982 and 2013 of senior unsecured bonds (the typical debt seniority in CLNs)
- S&P Recovery Rating of scale 4 for most reference entities in typical CDS indices, which S&P estimates a recovery rate between 30% and 50%

## 5.5 Single Name CLNs

Calculating the risk indicators of Single Name CLNs requires applying sections 5.1 and 5.4 above (as most Single Name CLNs do have market recovery).

### 5.5.1 VaR 99%

Using the DPs per year, in the year the cumulative DP increased above 1%, a default scenario in this year should be applied:

$$VaR\ 99\% = \frac{Notional\ Amount \cdot RR + Sum\ of\ previously\ paid\ coupons}{Issue\ Price} - 1$$

Where:

$RR = Estimated\ recovery\ rate$

If the cumulative DP does not increase above 1% the VaR 99% equals zero.

The VaR 99% is then inputted into the VaR volatility formula and mapped to a scale of 1 to 7 as described in section 2.1.2.

### 5.5.2 Average Downside

The average downside equals to:

$$\sum_{t=1}^T DP_t \times \left[ \frac{Notional\ Amount \cdot RR + sum\ of\ previously\ paid\ coupons_t}{Issue\ Price} - 1 \right] + \left( 1 - \sum_{t=1}^T DP_t \right) \times 0\%$$

Where:

$T = Total\ number\ of\ coupon\ periods$

$t = Coupon\ period$

$DP_t = Probability\ of\ default\ in\ period\ t$

$RR = Estimated\ recovery\ rate$

Then the absolute value of the averaged downside is inputted into the Black & Scholes equation as described sections 2.2.1 and 2.2.2.

## 5.6 Basket/Index Based CLNs

Calculating the risk indicators of zero recovery Basket/Index Based CLNs (e.g. CLNs based on Markit iTraxx or CDX index families) requires applying sections 5.1, 5.2 and 5.3. CLNs with market recovery require applying also section 5.4.

Here is a summary of the process:

- The DPs of the reference entities should be retrieved per coupon period (e.g. year) according to section 5.1.
- The distribution of credit events in each coupon period should be calculated based on sections 5.2 and 5.3, and then deriving the Outstanding Notional Amount distribution.
- The distribution of capital repayment and coupon payments should be computed by multiplying the coupon rate and the Outstanding Notional Amount for each period.
- For products with market recovery, section 5.4 should be taken into account.

### 5.6.1 VaR 99%

The distribution of product returns is computed based as described in the previous section, and the product return in the 99<sup>th</sup> percentile is the VaR 99%, which is then inputted into the VaR volatility formula and mapped to a scale of 1 to 7 as described in section 2.1.2.

### 5.6.2 Averaged Downside

The averaged downside is computed similarly to as described in section 2.2, while instead of running the Monte Carlo simulation, the return per percentile (i.e. confidence level) is calculated as described above (section 5.3).

## 5.7 Hybrid CLNs

In case of Hybrid CLNs, where the upside depends on another asset class (e.g. equity, interest rate), in addition to the calculation of the credit overlay described in the previous chapter, the upside should be added as follows:

- A Monte Carlo simulation should run on the option part as described in section 3 above.
- At this stage, for the simplicity of the calculation and for the minor impact, we assume no correlations between the credit overlay distribution and the upside component. Therefore, the option outcomes from the Monte Carlo should not be sorted, but left in the same order received by the random nature of the Monte Carlo, and added to a respective payout scenario of the credit overlay.
- For consistency, the Monte Carlo should consist of at least 10,000 scenarios.

### 5.7.1 VaR 99%

Similar to 5.6.1.

### 5.7.2 Averaged Downside

Similar to 5.6.2.