# Climate change valuation adjustment: introducing a climate change scenario extrapolation to long dated CDS curve

mazars

## The global climate crisis has triggered the financial sphere to address the way in which it conducts business. Climate risk consideration is currently growing in the banking industry but should also be considered by banks in the Credit Valuation Adjustment (CVA) when pricing derivatives.

The credit risk for long dated derivatives (beyond 10 years), reflected in Credit Value Adjustment, requires CDS curves that are only traded up to 10 years. Banks must resort to extrapolating these curves based on their own assumption (occasionally corroborated with auction trades or broker quotes). As climate change impacts long predated credit risk, a CDS curve extrapolation factoring climate change can be considered for counterparties most likely to be impacted.

The methodology introduced in the article to derive the climate change impact on CVA, namely Climate Change Valuation Adjustment (CCVA), is inspired by the article of (*Kenyon and Berrahoui 2021*). The following offers a second methodology based on an alternative extrapolation of the CDS curve derived from the adjustment of IFRS9 credit risk models to include transition risk scenarios.

The objective is to link the long-term credit risk impacted by a behavioural change in the market in response to the implementation of various policies aiming to transition towards a carbon-neutral economy. Transition risk refers to financial losses that a corporate may incur, directly or indirectly, because of the process of a lower carbon transition and a more environmentally sustainable economy. The potential impact of this transition risk on the CVA for the banking industry is highlighted in this article mainly focusing on European Corporates. As transition risk does not affect Financials and Industrials in the same way and intensity, the following sectors have been selected to represent the latter: Automobiles, Oil companies and Insurance & reinsurance companies.

# Methodology

Through this article, we aim to reflect climate change scenarios in the long-term credit risk when pricing CVA, by applying a factor which incorporates the climate transition risk impact on long term credit risk and the transmission of this impact to the CDS curve after ten years. To demonstrate this, there are two main components to our methodology:

1. Calculation of scenario dependent factors. Factors are derived from the ratio between the credit risk induced by transition risk scenarios, and a baseline scenario. For the rest of the article, factors are referred to as “Climate Change Credit Risk Ratio(s)”. The approach can accommodate any scenario, we have used three transition scenarios for illustration purpose. The scenarios are provided by external sources and reflects NGFS climate scenarios[1].
    a. A reference scenario known as ‘business as usual’ (S1), reflecting a scenario where no significant policies are implemented and resulting in higher temperature increase; in this scenario, the transition risk is reduced but the physical risks caused by higher hazard sinistrality

[1] https://www.ngfs.net/ngfs-scenarios-portal/

b. A second scenario (S2), one that is severe where the greenhouse gas emission reduction goals are not met in 2030, and drastic measures are then required to put in place immediately. This scenario is reproducing the disorderly transition NFGS's scenario.

c. A third scenario (S3), which is also severe and reproduces the NGFS disorderly transition scenario but starting earlier than S2 (in 2025). It assumes lower technological progress on the renewable energies and associates a revision of carbon price with a productivity shock on the whole economy compared to the reference scenario.

For each scenario, the external sources provided a list of macro-economic variables that were used to forecast the long-term credit risk up to 2050. The latter being measured by the forecast of the Probability of Default (PD) based on the adjustment of IFRS9 credit risk model.

2. Calculate the CCVA, using the Climate Change Credit Risk Ratios obtained in part 1. These ratios are applied to the CDS curve after ten years (for clarity, the derivatives in scope are long-dated swaps, with maturities of 30 years), which in turn are used to re-imply PDs adjusted for climate change.

We propose an adjustment of the CDS curve that can be used regardless of the approach used to stress the credit default probabilities used for Economic Credit Losses (ECL). To illustrate our approach, we use a macro economic stress testing of the counterparties, although much more granular approaches can be used, for example based on specific data on the balance sheet, strategies, etc. of the counterparties.

## Climate change credit risk ratio

The climate change credit risk ratio represents the evolution of the credit risk based on climate change transition risk during a time window. The methodology to calculate the latter is described in the graph below with further explanation given in the following paragraphs.

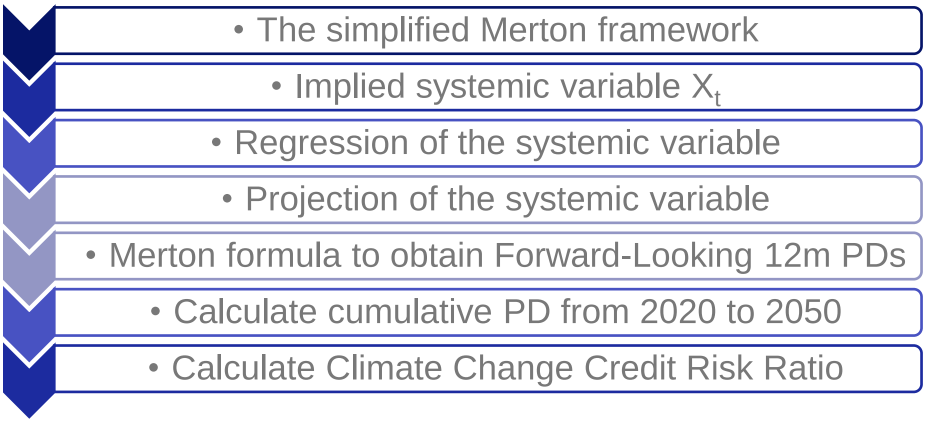


*Figure 1: Methodology steps for calculation of the climate change credit risk ratio*

The following methodology is applied to each sector of activity and each adverse scenario (S2 and S3).

## 1. 12m PD forecast methodology

To forecast the PDs up to 2050 under different climate scenarios and for each sector of activity, the forward-looking PD methodology used in IFRS9 framework was adjusted. The forward-looking methodology is based on a simplified form of the Merton model (see Equation 1). In this framework, a systemic variable $X_t$ which represents the macroeconomic environment is introduced. The sensitivity of the sector of activity to this systemic variable is obtained via the calibration of a correlation parameter $\rho$. Another parameter of the model consists of the yearly historical global corporate default rate, sourced from S&P (from 2005 to 2020), used to calculate the historical $X_t$ by regressing the latter over the yearly historical European Growth GDP sourced from the International Monetary Fund (IMF).

The $X_t$ forecasts are computed based on the projections of the corresponding yearly growth Value Added of each sector under each transition risk scenario in conjunction with the regression formula. The Value Added of a sector was selected as it is an economic productivity metric that measures the contribution of a sector and is used to adjust GDP.

$$\boldsymbol{PD_i(X_t^i) = \Phi\left(\frac{\alpha + \sqrt{\rho}X_t^i}{\sqrt{1-\rho}}\right)}$$

*Equation 1: 12m PD forecast using the Merton model*

Where:

- $\boldsymbol{i}$ represents the sector of activity
- $\boldsymbol{\phi}$ is the cumulative distribution function of a standard normal variable

We introduce coefficients $intercept_{GGDP}$ and $\beta_{GGDP}$ by regressing the historical $X_t$ derived from the yearly global corporate default rate (noted DR in the rest of the article) sourced from S&P[2] on the historical yearly European Growth GDP from 2005 to 2020. The coefficients of this linear regression are obtained through the ordinary least-square (OLS) method. The projections of $\boldsymbol{X_t^i}$ are obtained by the following equation, where $\boldsymbol{GVA_t^i}$ is the Growth Value Added of sector $i$:

$$\boldsymbol{X_t^i = intercept_{GGDP} + \beta_{GGDP} \times GVA_t^i}$$

- $\boldsymbol{\alpha}$ is derived from the historical average default rates $\boldsymbol{\overline{DR}}$ as $\boldsymbol{\alpha = \Phi^{-1}\left(\overline{DR}\right)}$[3]
- $\boldsymbol{\rho}$ is derived from the variance of the yearly historical default rates $\boldsymbol{\rho = \frac{Var[\Phi^{-1}(DR_t)]}{1+Var[\Phi^{-1}(DR_t)]}}$

## 2. Cumulative PD calculation

Using the forecasted 12m PDs, the annual cumulative PD is calculated, under each scenario and each sector as follows:

[2] Data obtained from the *Global Corporate Default Summary* table sourced from the S&P's 2020 Annual Global Corporate Default And Rating Transition Study
[3] Average of the historical yearly default rate from 2005 to 2020

$$CPD\,(T) = CPD\,(T-1) + \underbrace{\big(1 - CPD\,(T-1)\big)}_{survival\ probability} * \underbrace{PD\,(T-1, T)}_{PiT\ PD}$$

*Equation 2: Cumulative PD formula*

### 3. Climate change credit risk ratio calculation

Once the cumulative PD is calculated, the climate change credit risk (CCCR) ratio between two years is given by the ratio between the baseline and climate change scenario (S3 or S2 scenarios forecast from $Y_1$ to $Y_2$).

$$CCCR\ ratio = \frac{CPD_{Climate\ Change\ Scenario\ Y_2} - CPD_{Climate\ Change\ Scenario\ Y_1}}{CPD_{Base\ Y_2} - CPD_{Base\ Y_1}}$$

*Equation 3: CCCR ratio formula*

The ratio represents the relative increase in credit risk of the sector from $Y_1$ to $Y_2$ under a climate transition risk scenario, compared to the baseline.

Note that in this article, $Y_1$ = 10 years and $Y_2$ = 30 years.

## CCVA calculation

The products for which CVA and CCVA were computed on consisted of a range of long-dated uncollateralised Interest Rate Swaps. For each counterparty (CP), EURIBOR fixed-float swaps were chosen at varying moneyness:

- EURIBOR fix-float At-The Money (ATM) swap, 30-year maturity
- EURIBOR fix-float In-The-Money (ITM) swap, 30-year maturity
- EURIBOR fix-float Out-The-Money (OTM) swap, 30-year maturity
- EURUSD cross-currency ATM swap, 30-year maturity

In a nutshell, the CVA is computed with a standard CDS curve, using flat extrapolation beyond 10 years, and the CVA is computed similarly, but with a climate change adjusted CDS curve. The difference between these two CVA computations is defined as the CCVA.

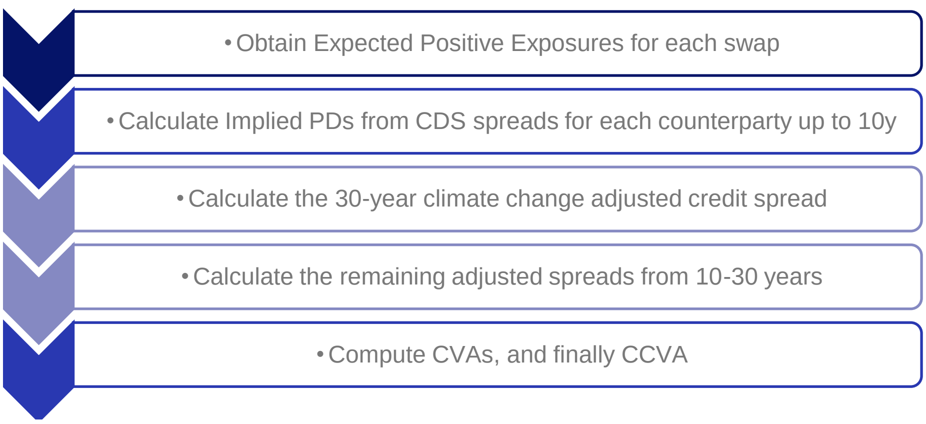


*Figure 2: Methodology steps for calculation of the CCVA*

Within each sector, a selection of corporates was chosen as the counterparty for each of the four swaps considered; these are shown in Table 1 below.

| Sector | Selected Counterparties |
|---|---|
| Oil & Gas | Total<br>BP Plc<br>Shell<br>Exxon |
| Automobile | Renault<br>Toyota<br>Volkswagen |
| Insurance | Allianz<br>Aviva<br>Scor<br>SwissRe |

*Table 1: Selected counterparties across each segment*

The following methodology is applied for each type of swap, counterparty, sector of activity and each adverse scenario (S2 and S3).

### 1. Expected Positive Exposure (EPE)

The EPE profile is obtained from Bloomberg for each type of aforementioned swap. Mathematically, the time- $t$ EPE of an IRS, given a time-0 starting point, can be expressed as the following:

$$\mathrm{EPE}_t \coloneqq E^t[D(0,t) \cdot max(MtM(t), 0)]$$

- $D(0,t)$ is the discount factor at time $t$
- $MtM(t)$ is the mark-to-market value of the swap at the future time point $t$
- $E^t$ denoted expectation under the $t$ –forward measure, which has $D(0,t)$ as its numeraire

The EPE "profile" is obtained by calculating the EPE at each future point $t_i$, where the $t_i$s define the grid for which the CVA is computed.

### 2. Implied PDs

The chosen counterparties all had quoted Credit Default Swaps (CDS) on Bloomberg for up to 10 years. The CDS curve for each CP coupled with the appropriate EUROIS discounting curve were used as inputs, from which the implied default probabilities were obtained via the standard 'bootstrapping' approach. A standard recovery rate of 40% has been assumed in this scenario.

The PDs obtained here represent the default probabilities in the "base" case, before modelling the impact of Climate Change.

## 3. CC Adjusted PDs

Upon obtaining the implied PDs for the base case, Mazars applied the following methodology to derive CC Adjusted PDs, which involves defining a term structure for the hazard rate past 10 years. This will be referred to as the climate-adjusted hazard rate.

To determine the possible shape of the hazard rate beyond 10 years, Mazars considered bonds with maturities of between 10 and 30 years for each of the corporates listed in Table 1, with similar seniorities. The purpose was to see whether the Z-spread in bond markets displays a shape beyond 10y, that would indicate that the market is factoring in climate change. However, there was insufficient data to warrant a meaningful analysis; in most cases there were less than three long-dated bonds with maturities greater than 10 years, which was not enough to infer a shape for the Z-spread. Hence, Mazars assume linearity in the hazard rate past 10 years, as is outlined below.

The hazard rate is defined (Castellacci, 2012) as the function $t \rightarrow \lambda(t)$ such that, with $\tau$ the time of default, the following holds:

$$P(\tau > t) = exp\left(-\int_0^t \lambda(u)du\right)$$

The hazard rate is expected to be piecewise constant for up to ten years, on a partition of the time axis corresponding with where the data points for the CDS spreads lie, at one, three, five, seven and ten years. This is standard market practice for bootstrapping CDS curves to obtain PDs. Note that up to ten years, where market data is available, climate risk is implicit in $\lambda(t)$ since it is "priced" into the quoted spreads.

After ten years, Mazars expects that the climate adjusted hazard rate will increase linearly, with the gradient of the increase proportional to a climate change component. Explicitly,

$$\lambda^{CC}(t) = \begin{cases} \lambda_i, & t \in (T_{i-1}, T_i], \quad T_i \leq 10 years \\ \lambda_{10yr} + \dfrac{t - 10}{20} \cdot \Delta\lambda, & t > 10 years \end{cases}$$

Where each $\lambda_i$ is constant, each pillar $T_i$ is a point for which CDS spreads exist in the market, $\lambda_{10yr}$ is the hazard rate at 10 years, and finally, $\Delta\lambda$ is the climate change component which is calibrated using the CCCR Ratio defined in Section 0.

The naïve assumption used to calculate the baseline PDs is that the hazard rate after 10 years is constant and takes the value $\lambda_{10yr}$, written as follows for $\lambda^{B}(t)$:

$$\lambda^B(t) = \begin{cases} \lambda_i, & t \in (T_{i-1}, T_i], \quad T_i \leq 10 years \\ \lambda_{10yr}, & t > 10 years \end{cases}$$

### 1.1. Calibration of *Δλ*

Rewriting the right-hand-side of Equation 3 in terms of the hazard rate gives an equation in terms of one unknown, $\Delta\lambda$, therefore the equation can be solved exactly. The main steps are outlined below:

$$CCCR\ ratio = \frac{CPD_{Climate\ Change\ Scenario\ Y_2} - CPD_{Climate\ Change\ Scenario\ Y_1}}{CPD_{Base\ Y_2} - CPD_{Base\ Y_1}}$$

$$= \frac{P^{CC}(\tau > Y_2) - P^{CC}(\tau > Y_1)}{P^{B}(\tau > Y_2) - P^{B}(\tau > Y_1)}$$

$$= \frac{exp\left(-\int_{Y_1}^{Y_2} \lambda^{CC}(u)du\right) - 1}{exp\left(-\int_{Y_1}^{Y_2} \lambda^{B}(u)du\right) - 1}$$

$$= \frac{exp\left(-\int_{10}^{30} \left(\lambda_{10yr} + \frac{t-10}{20} \cdot \Delta\lambda\right) du\right) - 1}{exp\left(-\int_{10}^{30} \lambda_{10yr} du\right) - 1}$$

$$\rightarrow \Delta\lambda = -\frac{1}{10}\ln(1 + \mathbf{CCCR\ ratio} \cdot (exp(-20\lambda_{10yr}) - \mathbf{1})) + \mathbf{20} \cdot \lambda_{10yr}$$

Now the hazard rate $\lambda^{CC}(t)$ is fully defined for all $t$, where it has been calibrated from the CDS market up to ten years, and then from ten to thirty years it is calibrated historically via the CCCR ratio. To obtain the CC adjusted PDs greater than ten years, we can use the following formula, shown directly through the hazard rate definition.

$$P^{CC}(\tau > 30) = P^{CC}(\tau > 10) \cdot exp\left(-\int_{10}^{30} \lambda^{CC}(u)du\right)$$

The approach that has been used is generic and can accommodate any climate risk scenario. It is also worth noting that an alternative approach would be to look at the Z-spread for long-term versus short-term bonds with the aim of inferring how climate risk is priced directly in the market. However, this would require further assumptions, for example on the term structure of the bond-basis, hence the proposed approach.

a. CVA

For simplicity, a Unilateral CVA formula is used which has several key assumptions, for example independence between interest rates and credit. This can be written as (Brigo, 2021):

$$\mathrm{CVA} = (1 - R) \cdot \sum_{i=0}^{n-1} EPE(t_i) \cdot (P^B(\tau > t_i) - P^B(\tau > t_{i+1}))$$

$R$ is the Recovery Rate (assumed to be 40%), and $P^B(\tau > t)$ are defined as in the previous section.

b. CVA$^{CC}$

Analogously, the CVA$^{CC}$ uses the same assumptions, except that rather than using the base default probabilities, the CC adjusted PDs ($P^{CC}(\tau > t)$) are used. This gives the following formula:

$$CVA^{CC} = (1 - R) \cdot \sum_{i=0}^{n-1} EPE(t_i) \cdot (P^{CC}(\tau > t_i) - P^{CC}(\tau > t_{i+1}))$$

c. CCVA

Finally, the CCVA is computed as the difference between the CVA and the CVA$^{CC}$. That is,

$$CCVA = CVA - CVA^{CC}$$

# Results

## Climate Change Credit Ratio results

The CCCR ratios resulting from the methodology are displayed in Table 2 below.

| Sector of activity | Ratio S3 / Baseline | Ratio S2 / Baseline |
|---|---|---|
| Insurance & reinsurance company | 104.20% | 100.80% |
| Automobiles | 100.10% | 100.20% |
| Oil & Gas | 137.70% | 181.00% |

*Table 2: PD Ratio results across sectors and climate risk scenarios*

The results show that the most impacted sector of activity by transition risk measures is the Oil & Gas, as expected. The S2 scenario impact is 32% higher than from the S3 scenario, this highlights that the timing and the way that policies are being settled can have a material impact on long term credit risk. On the contrary, the Insurance and the Automobiles sectors are minimally impacted by transition risk scenarios. The latter can be explained by the future technological improvements that will support the transition to a lower-carbon economy. For example, the development of technologies, such as renewable energy, battery storage, and carbon capture, will boost certain Industries, such as Automobiles.

In short, the transition risk impact highly depends on the sector of activity as well as the transition risk scenario, which is expected, as the impact on the long-term credit risk is very sensitive to those parameters. However, there are several limitations to be considered:

- The regression used to forecast the PD under different climate scenarios only uses one variable, the EU GGDP. More complex models with use of multiple macroeconomic variables (e.g., greenhouse gases emission, oil price...) could have highlighted different aspect of the credit risk under those climate scenarios.
- The climate scenarios only consider the transition risk scenarios, the physical risk is not included in those climate scenarios and may have a significant impact.

The climate risk field is constantly evolving, with new scenarios and more advanced climate models being developed. The climate scenarios considered in the article have been developed in 2020 and may be outdated. The main interest of this article is to underscore the following points:

- Climate change is a factor with a potential material impact that needs to be considered, and to invest in climate risk models adapted to banking portfolios to provide the best plausible picture of the evolution of credit risk over the long term.
- Climate risk scenarios can easily be translated into a CDS extrapolation beyond 10y.CCVA results

An important metric used to assess the impact is the ratio of the CCVA and the baseline CVA, the latter being the CVA computed with flat extrapolation of the CDS curve after 10 years.

**CCVA across sectors**

The most notable impact on the change in CVA was within the Oil & Gas Sector. For the S3 climate change scenario, in 8 of the 16 Swap x Oil & Gas Counterparty pairs the CVA increased by over 50%.

The change was more severe in the S2 scenario, where 8 out of 16 Swap x Oil & Gas Counterparty pairs saw an increase in CVA of over 50%. This was driven by the high values of the climate change credit ratio shown in Table 3.

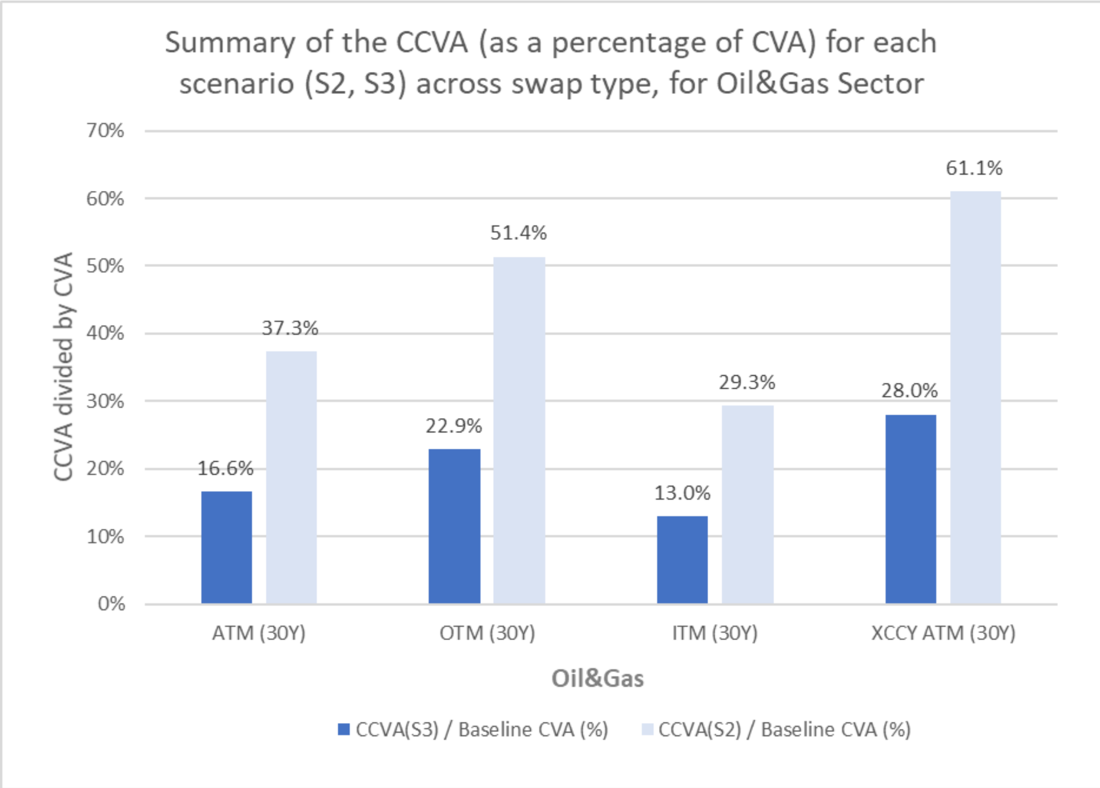


*Figure 3: A graph showing a summary of the CCVA (as a percentage of CVA) for each scenario (S2, S3) across each swap type, for the Oil & Gas sector.*

The impact across the remaining two sectors was far milder, with CCVA / Baseline CVA for both scenarios less than 1% for Automobiles, and for both scenarios less than 4% for Insurance. CCVA / Baseline CVA scales roughly linearly with the climate change credit ratio. In the Automobiles sector, this ratio was very close to 100% (100.1% and 100.2% in S3 and S2 respectively) and CCVA was very small. Oil & Gas on the other hand, where the climate change credit ratio was much larger, naturally saw CCVA being highly significant.

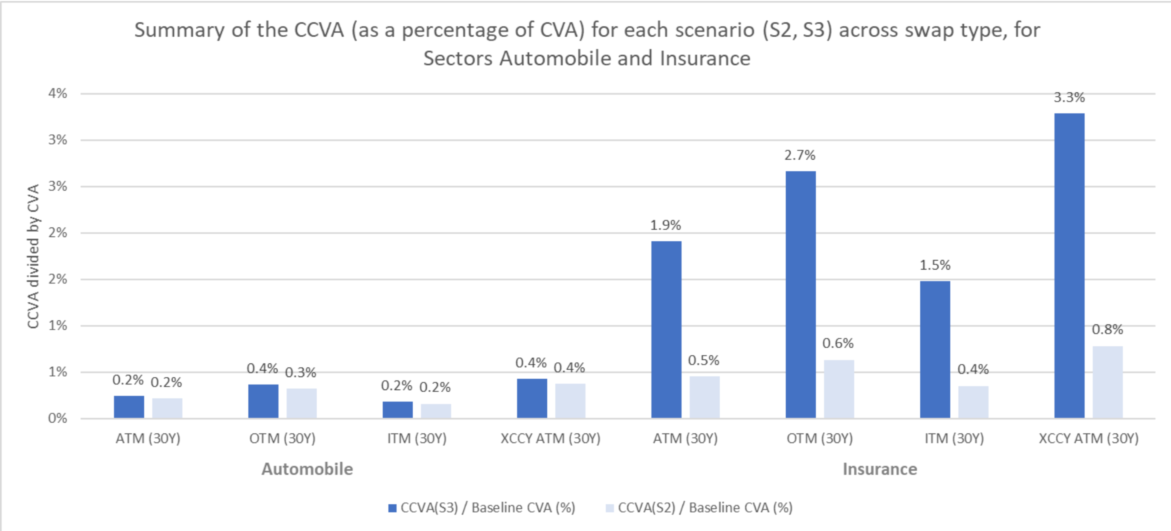


*Figure 4: A graph showing a summary of the CCVA (as a percentage of CVA) for each scenario (S2, S3) across each swap type, for the Automobile (left) and Insurance (right) sectors.*

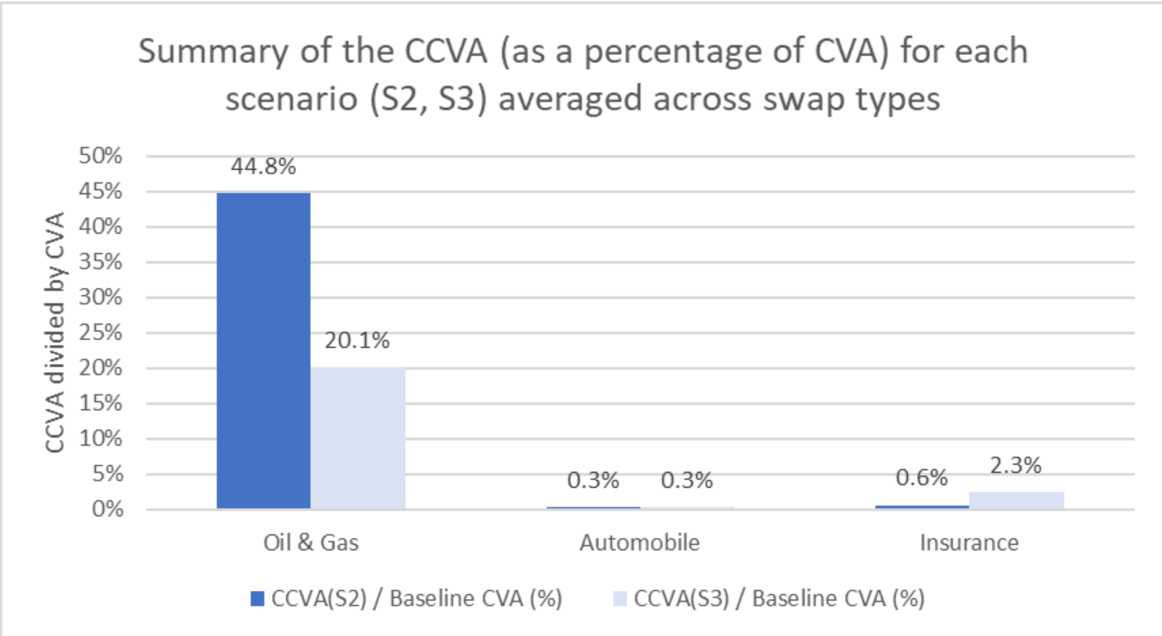


*Figure 5: Summary of the CCVA (as a percentage of CVA) for each scenario (S2, S3) averaged across swap types*

**CCVA and swap moneyness**

In-the-money swaps carry the highest absolute CCVA, but the lowest CCVA/Baseline metric, which is the CCVA scaled for the baseline CVA. The opposite is true for out-the-money swaps.

This can be explained through the Exposure Profile of each type of swap.

Since CVA is concerned with the integrated EPE with respect to the PD, the area under the curve (AUC) up to a time $t$ can be used as a measure to assess 'how much' exposure there is before $t$. Since climate change only impacts the PD after 10 years, we take $t = 10$, and calculate the ratio of the AUC up to 10 years with the total AUC. Figure 6 demonstrates that for an OTM swap, the exposure is more concentrated when it is closer to maturity, with a ratio of just 29%. Figure 7 shows the opposite for ITM swaps, where the ratio is 56%. Therefore, in the OTM case, there is a greater relative impact of CCVA, since most of the exposure is concentrated at a point in time that is impacted by climate change. The reverse holds for the ITM swap, which explains the lower CCVA/Baseline in this case.

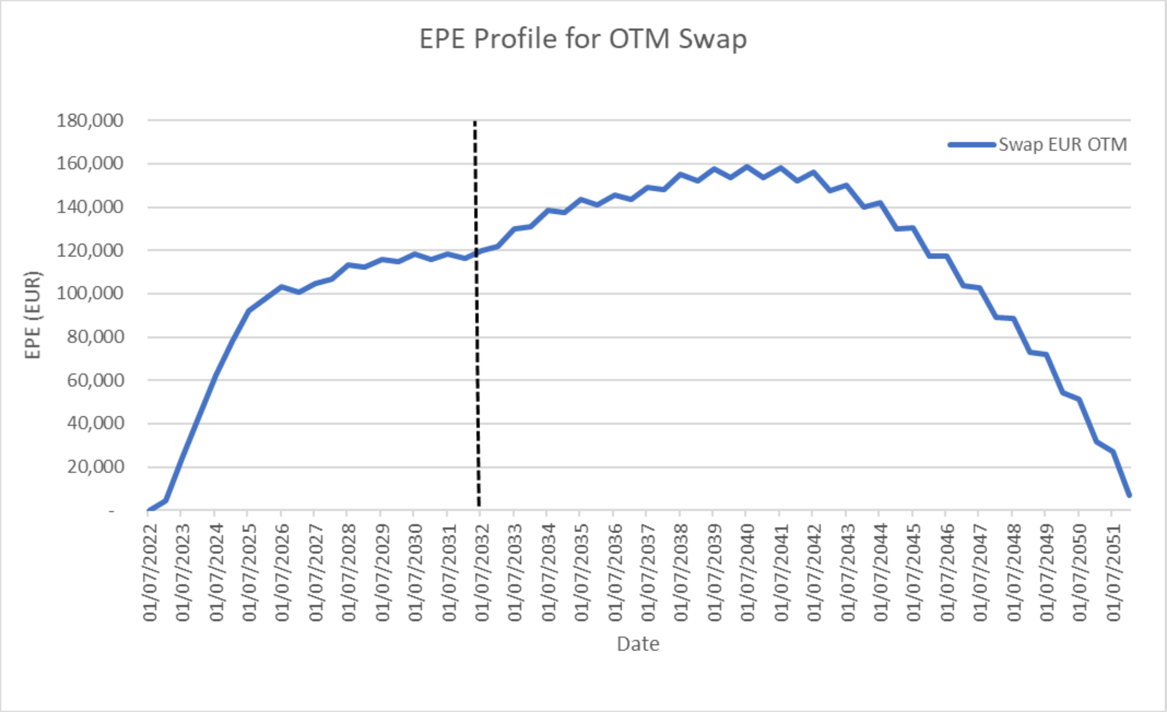


*Figure 6: Exposure profile for the OTM swap. The black dashed line marks the point for which climate change impacts the default probabilities*

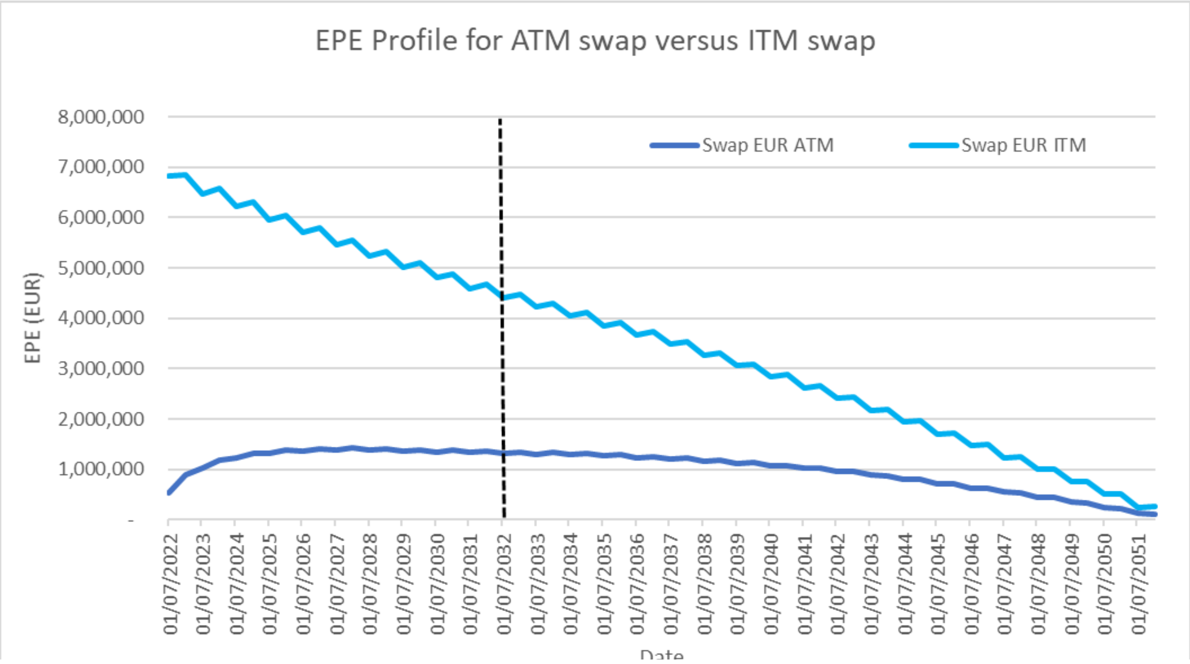


*Figure 7: Exposure profile for the OTM swap. The black dashed line marks the point for which climate change impacts the default probabilities*

# Conclusion

This article, based on the work of (*Kenyon and Mourad* 2021), aims to address an alternative way to account for the climate change impact in the credit spread of a counterparty by extrapolation in the long-term. The impact that the climate has is estimated through the computation of a climate change credit ratio, between a 'business-as-usual' situation and climate adverse scenarios, under IFRS9 framework.

Assessing the impact of climate change on CVA has shown that the consideration of climate scenarios is crucial. The results on the impact of considering a climate adverse scenario compared to a 'business as usual' scenario on the counterparty credit quality is materially significant, with an increase ranging from 1% to 80% depending on both:

- The sector of activity, demonstrating that climate risk consideration will shape credit marketing strategy in the long term.
- The climate scenarios, as credit risk is highly sensitive from one scenario to another. Both banks and governments should assess the different potential impacts to undertake the necessary measures to mitigate the latter.

Similarly, the impact of CCVA is highly sensitive to product trade economics: maturity of course but also moneyness.

Overall, this article raises awareness of how important it is to develop appropriate climate models and governance to mitigate the impact of climate change. This can be relevant to consider in wide variety of financial fields:

- Risk management, by assessing the impact of climate change in portfolio valuation as well as giving directions on the future credit marketing strategies.
- Accounting, by assessing future losses that may occur directly or indirectly, because of the process of a lower carbon transition or a more environmentally sustainable economy.
- Regulators, by including a climate change extrapolation of CDS spread in the calculation of prudential valuation.

# Bibliography

Brigo, D. (2021). *Interest Rate Models with Credit Risk, Collateral, Funding Liquidity Risk and Multiple Curves.* Imperial College London.

Castellacci, G. (2012). On Bootstrapping Hazard Rates From CDS Spreads. 2.

Kenyon, C., & Berrahoui, M. (2021). Climate Change Valuation Adjustment (CCVA) Using Parameterized Climate Change Impacts .