MILLIMAN WHITE PAPER

Consistent equity risk-neutral valuation under climate stress tests

Sophian Mehalla
Grzegorz Darkiewicz
Michal Krzeminski
Céline Francony

Effects of climate change are more and more noticeable, and notably impacts on economic activity. Economic scenarios representing the future possible states of economies are at the core of the regulatory calculations performed by insurance companies. This paper proposes a methodology for simulating proper risk-neutral scenarios used to perform Best Estimates calculations that integrate some climate transition risk.

Climate change is now having a significant impact on our daily lives. The sixth cycle synthesis report of the Intergovernmental Panel on Climate Change (IPCC) revealed that the average temperature has already risen by 1.1°C since 1900 (see IPPC in References section below). This global warming is largely attributed to human activities, in particular greenhouse gas emissions. In 2015, the Paris Agreement set a crucial target to keep temperature rises below 2°C. To achieve this, the signatory states pledged to go "carbon-neutral" as quickly as possible, and the European Parliament set this commitment for 2050. Companies, individuals and policies will have to evolve and modify their strategies to respect this pact. Those evolutions shall induce some "transition risk" that may impact all the sectors of the economy. In particular, significant impacts on the valuation of the assets held by insurers and more generally on their balance sheets are expected.

Consequently, this transition risk may exacerbate the market risk insurers are already exposed to as market agents shall integrate this risk into their anticipations. In particular, investors would avoid investing in possible future stranded assets, which can be expressed in brutal movements in assets prices or credit spreads of some companies.

Since 2020, regulators such as the French Prudential Supervision and Resolution Authority (ACPR) in France, the European Insurance and Occupational Pensions Authority (EIOPA) for the EU, the Bank of England in the UK and the Federal Reserve (FED) in the US have been conducting pilot climate exercises to integrate climate risk into insurance procedures and measure their impact on balance sheets. (For more information, see ACPR, EIOPA, BoE and FED in References.) Scenarios on the possible future states of the economies delivered by economic scenario generators (ESGs) are the core of the valuation process of undertakings' balance sheets. Notably, they are used to value in a *market-consistent* fashion the commitments of a company that are exposed to interactions between assets and liabilities.

In this paper, we examine different approaches to integrating climate risk in risk-neutral trajectories of equities and analyse their impacts on a virtual insurer's balance sheet. We have considered a European company whose balance is mainly driven by Euro Stoxx 50. The main aspect of our work has consisted in setting a modelling framework at the relevant granularity, taken from the European taxonomy. Consequently, in some experiments we will decompose the Euro Stoxx 50 by sector of activities, following the EIOPA's classification. Our work is based on the values of shocks provided by EIOPA in the Institutions for Occupational Retirement Provision (IORP) 2022 climate stress results, to be applied to the asset returns according to their sector of activity. In total, 13 sectors have been derived. (See EIOPA in References.)

To establish a relevant modelling granularity, several experiments have been led. The settings we consider in this paper are based on the following experiments:

1. In a first setup, the stress tests mentioned above are applied to the equity portfolio and the liabilities are valued by mapping all the model points to a unique equity factor generated by the ESG. We have focussed our study on an insurer that mainly operates on the European market and thus have chosen to calibrate this equity factor to the Euro Stoxx 50. This yields the reference method corresponding to common practices.
2. In the second setup, we tackle the incoherency of the reference method by valuing liabilities using separate equity risk factors: the ESG will generate as many equity paths as there are economic sectors included in the company's portfolio. In this experiment, all equity risk factors (sector indices) have the same volatility structure that is set equal to the one of the Euro Stoxx 50 (as in the first experiment). The correlation structure between sector indices is necessary in this experiment.

3. In the third setting we consider we propose to differentiate the volatility structure of each sector index by assigning to each equity risk-factor a proper volatility structure.

In experiments 2 and 3, we can assess the materiality of the sector-based calibration.

1. Finally, we propose to perform some sensitivity regarding 3 above. We will modify the volatility structure obtained in experiment 3 by applying some shocks on the volatility parameters, based on the discussion in the study “Return Volatility, Correlation, and Hedging of Green and Brown Stocks: Is There a Role for Climate Risk Factors?” (See LBGF in References.)

Because most climate stress tests do not specify how volatilities are impacted, this fourth step would aim to assess the materiality of stressing the volatility assumption.

To lead this work, the stochastic scenarios have been generated by Milliman Economic Scenario Generator.[1] The asset-liability management (ALM) run has been performed by Agile Model Milliman Agile ALM.[2]

Equity paths and sector-based indices: Settings

Risk-neutral modelling consists of simulating the future flows of an asset in a market-consistent way. Assuming a complete market with no arbitrage opportunities, the risk-neutral probability is unique and makes the discounted values of assets martingales. Risk-neutral economic scenario generators are used to evaluate the Best Estimate (BE) of life insurance liabilities. In this work, we have used the risk-neutral model volatility to generate equity paths is the Black-Scholes model with time varying.

DATA

As mentioned above, we perform our study based on the Euro Stoxx 50 (STX). In run 1, only one equity risk factor is simulated, and its volatility structure is calibrated to STX implied volatilities of at-the-money (ATM) European call options quoted on the market as of 31 March 2023, over maturities 1 to 20. Because runs 2 to 4 are associated with sector-based calibration, we also need data regarding the composition of the Euro Stoxx 50 per sector of activity, using the index’s Statistical Classification of Economic Activities in the European Community (NACE) codes. To conduct this study, we used the stocks making up the Euro Stoxx 50 index, which comprises the 50 largest market capitalisations in the Eurozone. The shock applied for this study comes from the EIOPA table drawn up in April 2022 for the IORP stress tests (see EIOPA in References). The Euro Stoxx 50 comprises 13 different sectors, defined by the NACE code groupings drawn up by EIOPA. The equity portfolio of the virtual company we have considered is thus composed of 13 assets in the ALM runs.

We have tested four approaches to integrating climate risk into risk-neutral equity scenarios. The four methods differ in their granularity, and we will introduce them from the most general to the most detailed.

SETTING NO. 1

The first approach is a standard one, in which the equities of the undertaking portfolio are all mapped to a single equity risk factor that is the Euro Stoxx 50. In this approach, the volatility structure is identical for all sectors, corresponding to that of the Euro Stoxx 50.

The equity factor, whose value at time t is denoted by S_t, is modelled using Black-Scholes model with time-varying volatility. In the risk-neutral universe, this equity evolves as:

$$\frac{\mathrm{d}S_t}{S_t} = r_t \mathrm{d}t + \sigma(t)\mathrm{d}W_t^S,$$

where r_t is the (time-t) value of the short risk-free rate and W^S is a Brownian motion leading the evolution of the equity factor.

The function $t \mapsto \sigma(t)$ is piecewise constant and is calibrated to market data. More precisely, it is determined using Euro Stoxx 50 implied volatilities of ATM European call options quoted on the market as of 31 March 2023, over maturities 1 to 20.

[1] See https://www.milliman.com/products/economic-scenario-generator.
[2] See https://www.milliman.com/en/products/milliman-agile-alm.

SETTING NO. 2

In the second approach proposed, we classify the 50 undertakings composing the Euro Stoxx 50 according to its sector of activity (using its NACE codes). We obtained then 13 groups of stocks, as depicted in the table in Figure 1, that will be modelled and simulated by Milliman ESG. NACE indexing is a standardised classification system for economic activities at the European level. NACE codes can be found either on the European Commission websites[3] or in information on economic activities reported by companies in their annual reports (see Reports in References). Where a company has several attributed NACE codes, we have proceeded as follows:

- We preferably identify the main activity of the company and attribute the NACE code of it to the undertaking; If not possible, because the various activities are equally weighted or because the names of the activities cited in the annual report correspond to several NACE codes, we assign to the undertaking the NACE code associated with the most unfavourable EIOPA shock.

FIGURE 1: ANALYSIS OF THE EURO STOXX 50 BY NACE CODE

NACE CODES	BRIEF DESCRIPTION	NUMBER OF COMPANIES IN STX	WEIGHTS[4] IN STX (%)	RELATIVE SHOCK IN EQUITY PRICES (%)
A01	Animals	0	0,0	-11,5
A02-A03	Logging, fishing	0	0,0	-11,8
B05-B09	Extractive industry	2	6,1	-37,8
C10-C12	Food	3	4,1	-12,3
C13-C18	Luxuary	5	11,9	-10,9
C19	Petroleum refinery	0	0,0	-32,2
C20	Chemical	3	6,3	-12,7
C21-C22	Pharmaceutical	1	3,4	-11,1
C23	Manufactory of non-metallic mineral products	0	0,0	-20,4
C24-C25	Manufactory of metal products	0	0,0	-15,3
C26-C28	High-tech manufactory	5	17,2	-11,1
C29-C30	Aviation	2	4,1	-11,2
C31-C33	Other manufactory, reparation	0	0,0	-9,8
D35	Electricity production	3	6,0	-23,0
E36-E39	Water and waste treatments	0	0,0	-13,1
F41-F43	Building, networks	2	2,8	-11,5
G45-G47	Cars	6	7,1	-13,4
H49	Transport and storage	1	1,3	-22,6
H50	Water transport	0	0,0	-12,7
H51	Air transport	0	0,0	-14,2
H52-53	Warehousing and postal services	0	0,0	-10,8
L68	Real Estate	1	0,6	-12,0
Other	Bank, insurance	16	29,2	-14,3

[3] See Search on Competition (europa.eu) or EUROPA - Competition - Cases by NACE code - A.
[4] See EURO STOXX 50: EURO STOXX 50 Index components | MarketScreener.

For modelling requirements (see below), we also need information on the composition of the Euro Stoxx 50 index and on the specific volatilities structure of each company composing it. However, to our knowledge, there exists no broad market quotation of implied volatilities on European options whose underlyings are company equities; such data only exists for indices. For this experiment and the following one, we have thus relied on a historical approach still with the market-consistency requirement, while degraded. The volatility structures of the 50 stocks were obtained thanks to Refinitiv data provider over the period 2 January 2002, to 31 May 2023. The data was sampled monthly, providing 256 quotation dates. To reconstitute the index, we used the weights of each stock from the Marketscreener platform on 30 May 2023. In the calculations, we will consider these weights to be time-independent. This last choice is a simplification as the weights and the composition of the Euro Stoxx 50 vary over time.

In formulas, this second experiment is described as follows: let S_t^i be the value at time t of the i-th share of the Euro Stoxx 50 index and ω_i be its corresponding weight. With these notations, the value of the Euro Stoxx 50 index at time t can be written as:

$$S_t = \sum_{j=1}^{50} \omega_j S_t^j.$$

As explained above, we pool those 50 stocks by sector of activity to obtain 13 indices we will refer to as “sector indices.”
The sector of activity (i.e., NACE code) I is represented by the normalised index defined as:

$$A_t^I := \frac{1}{\overline{\omega}_I} \sum_{i \in I} \omega_i S_t^i \ \ (1)$$

where $\overline{\omega}_I = \sum_{i \in I} \omega_i$.

In term of sector indices, the Euro Stoxx 50 index thus writes as:

$$S_t = \sum_{I=1}^{13} \overline{\omega}_I A_t^I . (2)$$

Those 13 sector indices are modelled by Black-Scholes dynamics again:

$$\frac{\mathrm{d}A_t^I}{A_t^I} = r_t \mathrm{d}t + \sigma(t) \mathrm{d}W_t^I \ \ (3)$$

where r_t still denotes the time-t value of the risk-free short rate, the W^I are standard Brownian motions under risk-neutral probability and the function $t \mapsto \sigma(t)$ is retaken from run 1, that is, it is coming from a calibration to the Euro Stoxx 50 volatility structure.

Specifying the correlation structure between the sector indices $(A^I)_t$ still remains. We estimate the correlation between sector indices by considering historical series of discounted log-returns:

$$R_{t_k}^I = \ln \left[\frac{\frac{A_{t_k}^I}{1 + ERB(t_k, 1)}}{\frac{A_{t_{k-1}}^I}{1 + ERB(t_{k-1}, 1)}} \right]$$

where $\mathrm{ERB}(t_k, 1)$ is the value at date t_k of the 1-year Euribor.

The correlation between the Brownian motion W^I, driving the evolution of A^I, and the Brownian motion W^J, driving the evolution of A^J, is then set equal to the correlation measured between the historical series of log-returns:

$$\rho_{I,J} = \mathrm{Cor}(W^I, W^J) = \mathrm{Cor}(R^I, R^J).$$

Using historical data from 2 January 2002 to 31 May 2023, we calculated the empirical correlations between each sector given in Figure 2. First observe that all correlations are nonnegative in our experiments. It turns out that the greatest observed correlation is between sectors C13-C18 (luxury) and C26-C28 (high-tech products), which are two sectors that have experienced significant growth over the last years. On the contrary, the lowest measured correlation is about 14% and is observed between L68 (real estate) and the sector "Other" (mainly composed of insurances and banks).

FIGURE 2: CORRELATIONS BETWEEN SECTOR INDICES

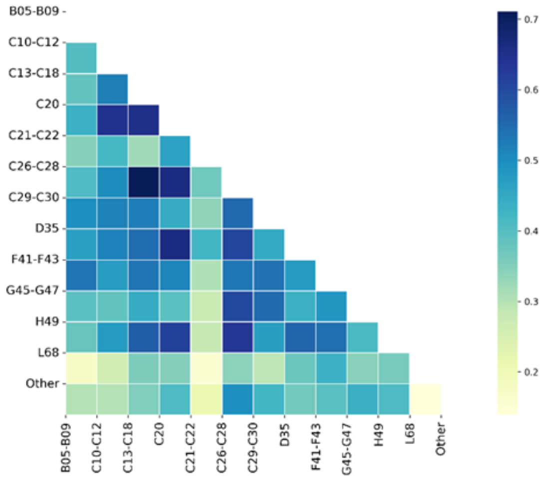
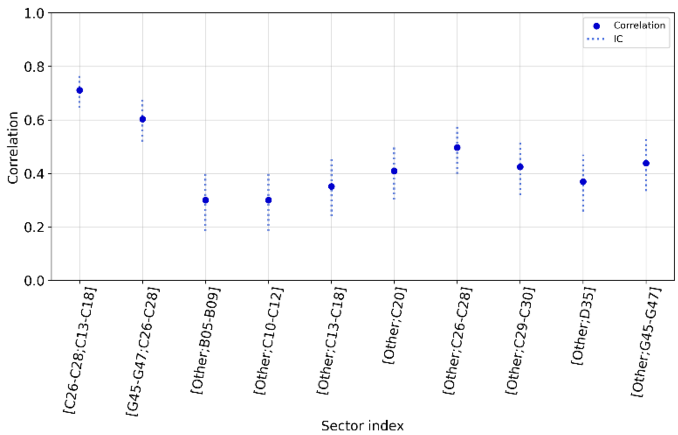


Figure 3 shows the correlations and 95% Fisher confidence intervals for the 10 pairs of sectors with the highest weights in the index (see Appendix A for more details).

FIGURE 3: INTER-SECTOR CORRELATIONS WITH 95% FISHER CONFIDENCE INTERVALS



SETTING NO. 3

In this third approach, we will still distinguish between sectors but, in addition, we now calibrate proper volatility to each sector index.

In formulas, equation 3 becomes, in present settings:

$$\frac{\mathrm{d}A_t^I}{A_t^I} = r_t \mathrm{d}t + \sigma_I \mathrm{d}W_t^I \ (4)$$

where σ_I is a positive coefficient that is the proper volatility of sector index I and must be calibrated.

As no quoted implied volatility exists of European options on sector indices (nor on the individual stock equities composing them), we have chosen to set the volatilities σ_I constant equal to the historical volatilities (estimated on monthly data before being annualised) estimated over the period from 2 January 2002 to 31 May 2023. Note that, in this setting, and contrary to the previous ones, there is no time dependency in the volatility structure. The obtained values are depicted in the table in Figure 4. We can observe that the aviation sector (C29-C30) is associated with the highest realised volatility while electricity production (D35) is the most “stable” sector.

FIGURE 4: ANNUALIASED MONTHLY VOLATILITIES BY NACE CODES

NACE Codes	Volatility (%)
B05-B09	20,17
C10-C12	16,56
C13-C18	22,09
C20	17,95
C21-C22	19,39
C26-C28	24,73
C29-C30	30,57
D35	16,02
F41-F43	22,19
G45-G47	26,14
H49	29,44
L68	25,52
Other	26,19

As explained above, sector indices volatilities come from historical estimations. To maintain consistency with market information (the so-called *market consistency*), we have chosen to modify the correlation structure given in Figures 2 and 3 so that the total volatility embedded in sector indices would be equal to the implied volatility on European options quoted on market (and used for the purpose of comparison with the first approaches, see runs 1 and 2 above). To do so, first observe that the volatility of the overall index defined in equation 2 is embedded in the paths simulated thanks to the model defined by equation 4, given by:

$$\sigma_{\mathrm{tot}}^2 = \sum_{I,J=1}^{13} \bar{\omega}_I \bar{\omega}_J \rho_{I,J} \sigma_I \sigma_J \,. (5)$$

We want to impose σ_{tot} to be equal to the average implied volatility of Euro Stoxx 50,[5] $\sigma_{STX50} = 19.91\%$. However, imposing this equality should be offset by the fact that we no longer can replicate all sector volatilities accurately. In other words, some degrees of freedom should be granted to ensure the wanted equality. We have chosen to maintain the weights $(\bar{\omega}_i)$, the historical volatility coefficients (σ_I) —see Figure 6— and to adjust the values of some of the estimated correlations $\rho_{I,J}$. To choose which correlation coefficients can be adjusted to ensure the wanted equality (5), we have proceeded as follows. The aim was to modify as few correlation coefficients as possible. However, we also wanted to have enough flexibility to accurately replicate the target volatility. We therefore selected eight coefficients and chose to modify the values of correlations between the sectors designated as "Other" by EIOPA, which are mainly composed of banks and insurance, and sector C26 to C28, related to the manufacture of computer,

[5] As we work here with constant parameters, we have chosen as target volatility the average ATM call options quoted implied volatility on Euro Stoxx 50 as of 31 March 2023, over maturities 1 to 10.

electronic, optical, electrical and machinery products. We have then performed an optimisation routine to find the “best” new coefficients that ensure equation 5 to be met. The fitted correlations are listed in the table in Figure 5.

FIGURE 5: MODIFIED CORRELATIONS BY SECTOR

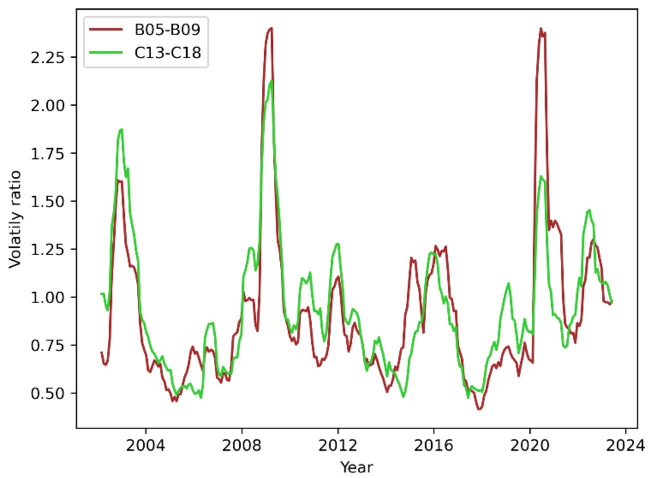
SECTOR	PREVIOUS CORRELATION	ADJUSTED CORRELATION
[C13-C18 x C26-C28]	0,71	0,85
[C13-C18 x Other]	0,35	0,90
[C20 x C26-C28]	0,66	0,83
[C20 x Other]	0,41	0,86
[C26-C28 x G45-G47]	0,60	0,86
[C26-C28 x Other]	0,50	0,90
[C29-C30 x Other]	0,42	0,85
[G45-G47 x Other]	0,44	0,84

SENSITIVITIES PARAMETRISATION

In additional experiments, we perform some sensitivities with respect to the previous run 3 setting. As the sector B05 to B09 is associated with the larger value of shock to be applied, we aim at performing some sensitivity with respect to the volatility parameter of this sector index. Symmetrically, we would like to assess the impact of changing the value of the volatility of the “greenest” sector index included in the Euro Stoxx 50, C13 to C18.

In the graph in Figure 6, we display the ratio between the six-month realised volatilities and the volatility estimated over the whole historical period (the latter being used in the run 3 configuration); this is done for the “brown” sector B05 to B09 (extractive industry) and the green one, C13 to C18 (textile industry). Note that the realised volatility is computed backward: at each date on the graph, the ratio is computed thanks to the realised volatility over the previous six months.

FIGURE 6: EVOLUTION OF 6-MONTH REALISED VOLATILITIES COMPARED TO THE FULL-PERIOD VOLATILITY



We observe that both ratios closely vary in the range of values, roughly [0.5, 2.3]. Not surprisingly, the ratios blow up during economic crisis. Motivated by the fact that “brown” assets may become less and less attractive for investors, as opposed to “green” assets (see for instance the discussion in LBGF in References), we have realised, in a conservative perspective, two sensitivities (gathered in table of Figure 7) in which we:

- Run 4: Double the volatility of the brown sector B05-B09
- Run 5: Divide by two the volatility of the green sector C13 C18.

FIGURE 7: ANNUALISED MONTHLY VOLATILITIES BY NACE CODE

NACE CODES	FORMER VOLATILITY (%)	STRESSED VOLATILITY (%)
B05-B09	20,17	40,34
C13-C18	22,09	11,05

PERFORMING THE SIMULATIONS

Milliman ESG was used to generate the necessary tables, which are then used as inputs to the ALM algorithm.

We generated tables containing 5,000 simulations of equity and interest rate trajectories over a 30-year horizon.

For zero-coupon rates, the maximum maturity considered is 30 years. The model used to model interest rates is the Libor Market Model (LMM) with a displaced diffusion calibrated to the curves and swaptions volatilities quoted on 31 March 2023 (source: Refinitiv).

Equity indices are modelled using a Black-Scholes model with constant piecewise deterministic volatility, whose setting is described in the previous section for each experiment.

Dividends are all modelled with a positive Cox-Ingersoll-Ross process with the same parameters for all three tables and all equity indices.

We have run simulations in a risk-neutral universe. To be valid, the simulated scenarios must verify certain properties. Two tests are therefore performed on the generated tables to ensure a satisfactory estimation of BEs:

- **Martingality tests**, which consist of verifying the fundamental hypothesis of the martingality of discounted prices in the risk-neutral universe;
- **Market consistency testing** of generated scenarios, which consists of comparing current market volatilities with the Monte Carlo volatilities estimated on the simulated paths.

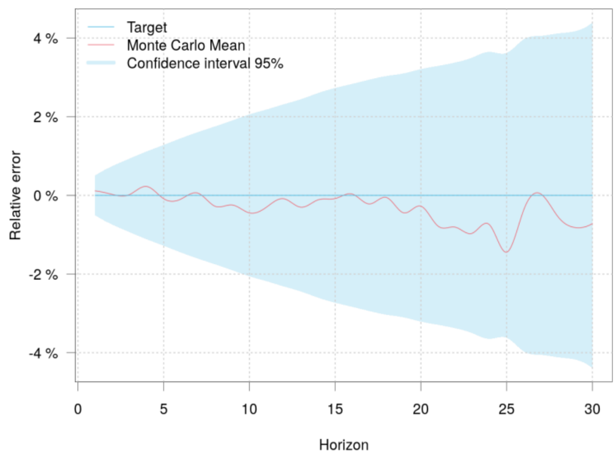
In this section, we present the results of these tests for the different economic scenarios that have been generated, representing the different approaches to integrating climate risk into risk-neutral trajectories of equities.

VALIDATION OF SETTING NO. 1

The first table corresponds to the reference method for applying an equity shock: a single equity factor with a volatility structure calibrated to the Euro Stoxx 50 implied volatility of ATM European call options. The starting level of equity trajectories corresponds to the level of the Euro Stoxx 50 on 31 March 2023.

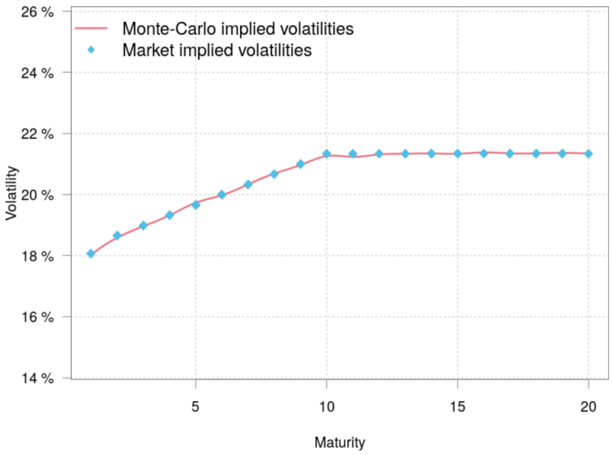
The result of the martingality test is illustrated in Figure 8. We observe that, over our 30-year projection horizon, the expected discounted values estimated by the Monte Carlo method are close to the initial value of the index, as the quantity $\frac{\mathbb{E}[\widetilde{S_t}]}{S_0} - 1$ remains within the 95% confidence interval through time (where $\widetilde{S_t}$ stands for the discounted value of S_t). The maximum relative deviation of martingale tests on the equity index is 1.44%: this martingality test is satisfactory.

FIGURE 8: MARTINGALITY TEST FOR RUN 1



The result of the market-consistency test for this experiment is illustrated in Figure 9. We note that the implied volatility estimated on the simulations is very similar to the market implied volatility structure, which validates this first set of scenarios.

FIGURE 9: MARKET CONSISTENCY TEST FOR RUN 1



VALIDATION OF SETTING NO. 2

The second table corresponds to a differentiation of the 13 equity factors according to sectors present in the Euro Stoxx 50 with a proper correlation structure. The volatility structure is still calibrated to the Euro Stoxx 50 implied volatility of ATM European call options. The starting level for equity trajectories corresponds to the level of the 13 sector indices on 31 March 2023.

In this section, we have 13 equity factors corresponding to the 13 sectorial indices, which means that we perform 13 martingality and market-consistency tests. We will only present the two tests that gave the least favourable results.

The results of martingality tests for the sector with corresponding NACE codes F41 F43 (equity #16) and G45-G47 (equity #17) are provided in Figures 10 and 11, respectively. Again, the expected discount values remain within the 95% confidence intervals over time. The maximum relative deviation of martingale tests on the equity index is 1.83% for sectors F41-F43 and 2.03% for sectors G45-G47.

FIGURE 10: MARTINGALITY TEST FOR RUN 2 – EQUITY FACTOR 16

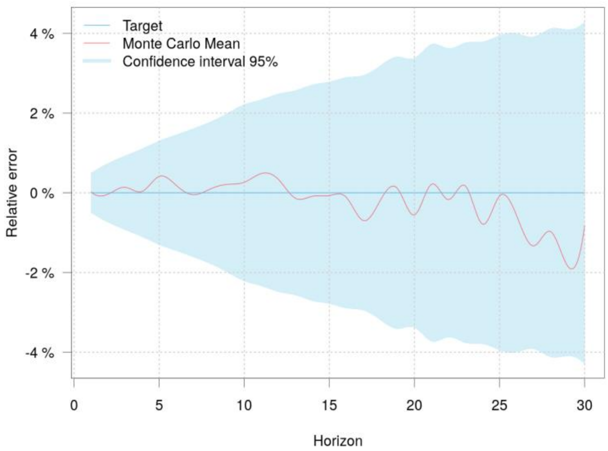
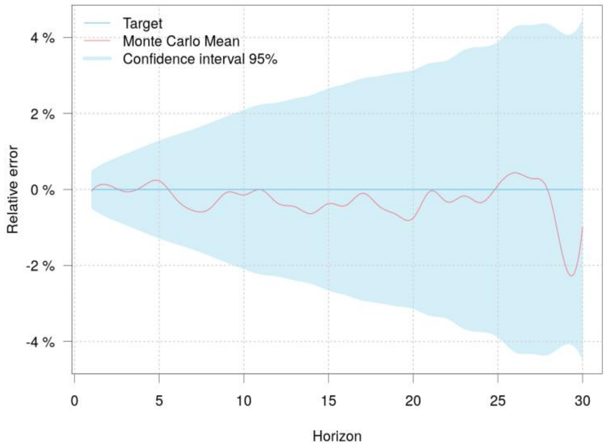
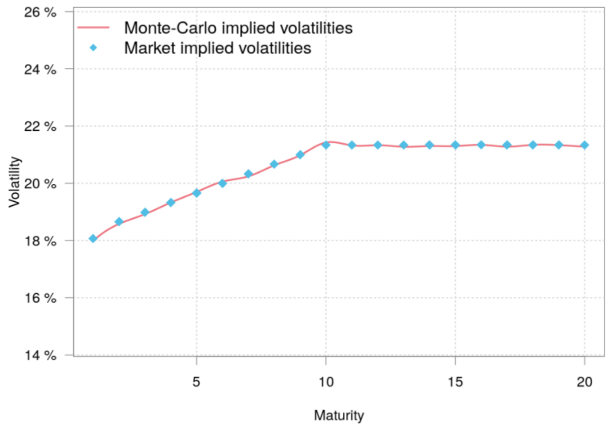


FIGURE 11: MARTINGALITY TEST FOR RUN 2 – EQUITY FACTOR 17



As the volatility structure is common to all 13 sectors modelled and is identical to the volatility structure used in run 1, the results of the market-consistency tests are common to all sectors (see Figure 12) and are the same as the previous one (depicted in Figure 9). Again, the replication of the volatility structure on simulations is very satisfactory.

FIGURE 12: MARTINGALITY TEST FOR RUN 2 – EQUITY FACTOR 16



VALIDATION OF SETTING NO. 3

The third table corresponds to a differentiation of the 13 equity factors according to sectors present in the Euro Stoxx 50, with now a proper volatility structure (derived from historical data) and a proper correlation structure (calibrated so that equation 5 is verified). The starting level for equity trajectories corresponds to the level of the 13 sector indices on 31 March 2023.

As with the second run, we will present the two tests that gave the least favourable results from the 13 available.

The results of martingality tests for the sector corresponding to NACE codes C29-C30 (equity #12) and H49 (equity #18) are provided in Figures 13 and 14, respectively. Estimated expected discounted values get closer to the bounds of the 95% confidence intervals at the end of the equity #12 simulation but remain within the confidence interval. The maximum relative deviation of martingale tests on the equity index is 5.08%.for sector C29-C30 and 3.88% for sector H49. Those tests are largely satisfactory.

FIGURE 13: MARTINGALITY TEST FOR RUN 3 – EQUITY FACTOR 12

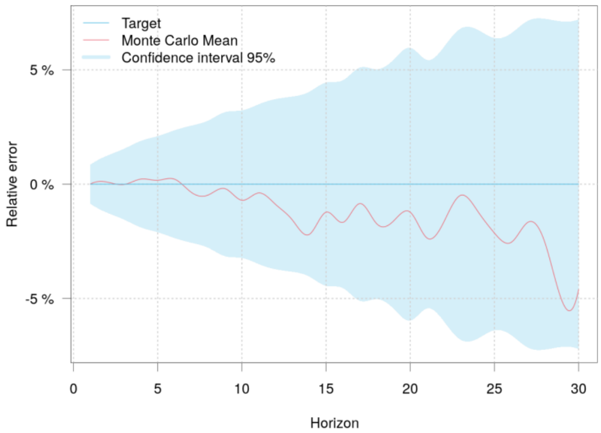
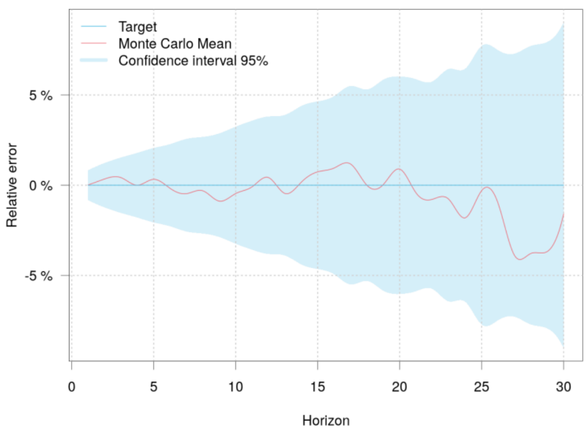


FIGURE 14: MARTINGALITY TEST FOR RUN 3 – EQUITY FACTOR 18



The results of the market-consistency tests are illustrated in Figures 15 and 16 (corresponding, respectively, to the C29-C30 and H49 sectors). In this experiment, we work with constant volatility structures, whose replications are very accurate over time.

FIGURE 15: MARKET-CONSISTENCY TEST FOR RUN 3 – EQUITY FACTOR 12

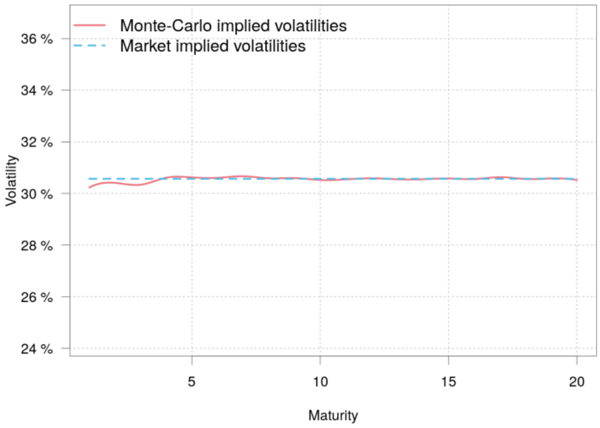
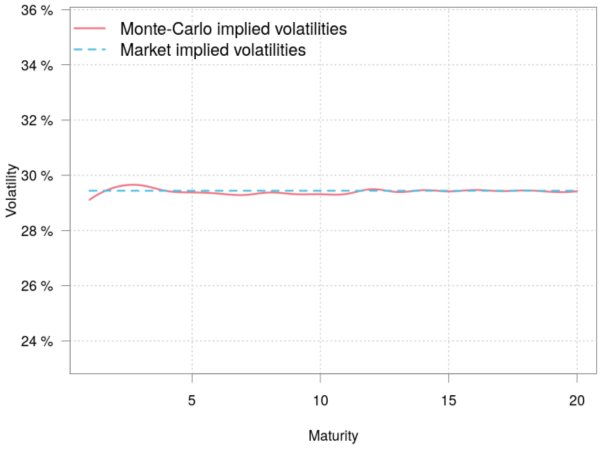


FIGURE 16: MARKET-CONSISTENCY TEST FOR RUN 3 – EQUITY FACTOR 18



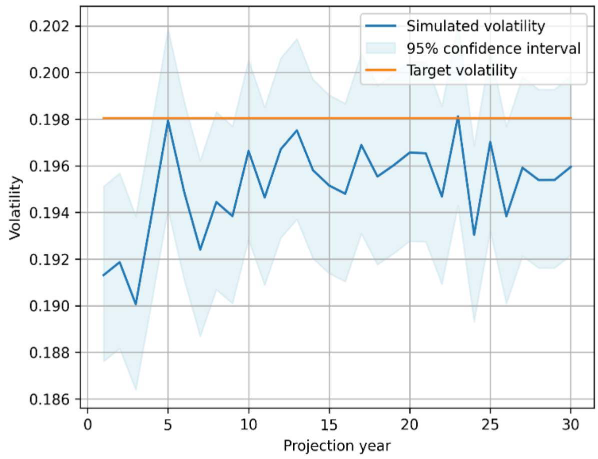
In this third approach, we provide an additional market-consistency test. As a reminder, in this method we have calibrated the correlations so that equation 5 is satisfied. In this way, we can compare the average implied volatility of the Euro Stoxx 50 (target volatility) — $\sigma_{\text{tot}} = 19.81\%$ — and the volatility estimated over the 5,000 simulations of the Euro Stoxx 50 index that has been recovered by aggregating the 13 sector indices and their associated weights (simulated volatility). We consider a 95% confidence interval around the estimated volatility built as:

$$IC_{\sigma} = \left[\sigma_e \times \sqrt{\frac{n-1}{\chi^2_{n-1,1-\frac{\alpha}{2}}}} \; ; \; \sigma_e \times \sqrt{\frac{n-1}{\chi^2_{n-1,\frac{\alpha}{2}}}} \right]$$

where σ_e is the simulated volatility, n is the number of simulations, $\chi^2_{m,x}$ is the x-quantile of the Chi-square distribution with m degrees of freedom and α is the confidence level (5%).

Figure 17 displays target and simulated volatilities over the 30 years of projections. We observe a good fit of the target volatility compared to estimations over time.

FIGURE 17: TARGET AND SIMULATED VOLATILITY OVER TIME



In this way, the scenarios generated by the ESG in the three experiments satisfy the martingale and market-consistency requirements of the risk-neutral universe and can be used to perform ALM runs.

ALM modelling

WORKING OF THE MODEL

We have calculated the reported values:

- Best Estimate of Liability (BEL or BE)
- Time Value of Financial Options and Guarantees (TVFOG),

in the base case and under a climate stress scenario for different calibrations of economic scenarios (experiments 1-4).

For these calculations we used an iterative approach using an Excel model for liabilities (products with profit participation) and the Milliman Agile ALM tool for asset projections.

We note that Milliman Agile ALM is more than simply an asset model, as it also captures the interactions between assets and liabilities with the same effect as a full dynamic ALM model. The calculation process is based on iterations to ensure a correct fitting of the assets and liabilities. In the iteration process, liabilities and ALM components are run interchangeably: after each liability run, the liability cash flows are imported by Milliman Agile ALM in order to process the assets, and after each ALM run projected investment returns are imported in the liability model in order to recalculate cash flows. After a couple of iterations, differences between two consecutive iterations become very small and the results converge to the projected liability cash flows. In fact, the cash flows resulting from the iteration process are exactly the same as the ones obtained with a full dynamic ALM model with the same parameterisation.

PARAMETRISATION

For this exercise we have considered an insurer with a profit portfolio of rather typical characteristics for some markets in the West Europe (e.g., France, Germany, Italy).

In the model we considered a mix of policies with different expiries (between one and 30 years) and different interest rate guarantees (0%, 1% and 2%), a fixed lapse rate of 5% without dynamic policyholders' behaviour and a profit-sharing formula which pays an excess of accounting investment returns about the sum of the interest rate guarantee and a fixed management fee of 1%, so that the total client return that is allocated to policyholders can be expressed by a formula:

$$\boldsymbol{TCR_t} = \mathbf{max}(\boldsymbol{IR_t} - \mathbf{1}\%, \boldsymbol{IG})$$

where *TCR* denotes total client return, *IR* investment return and *IG* interest rate guarantee.

Regarding the investment portfolio, we considered an asset allocation with 30% of assets allocated in equities according to assumed sector allocations (see the Results section below) and 70% of assets allocated in high-quality EUR government bonds. In the rebalancing process bonds are assumed to be sold starting from the shortest one while any cash excess is invested either in equities or in 15-year government bonds, depending on the actual asset mix versus the target asset mix.

Results

We have performed several ALM runs based on the previously described settings. Two asset allocations have been tested: they are given in the table in Figure 18. Note that, in all experiments, the total equity-related assets represent 30% of the total asset portfolio of the company.

FIGURE 18: RETAINED ASSET ALLOCATIONS

NACE CODES	ASSET ALLOCATION #1 (%)	ASSET ALLOCATION #2 (%)
B05-B09	1	50
C10-C12	3	1.5
C13-C18	5	2.5
C20	1	0.5
C21-C22	2.5	1.3
C26-C28	7	3.5
C29-C30	6	3.0
D35	3	0
F41-F43	3	1.5
G45-G47	1.50	0.8
H49	1	0
L68	1	0.5
Other	65	35.0

The first allocation is a benchmark one coming from our observations of the composition of some companies’ portfolios. The second allocation is a distortion in which we have overweighted the allocation of the “brownest” asset, modelled by the B05-B09 sector index; the other brown assets (D35, H49) have been removed from the portfolio and the remaining assets have been redistributed proportionally.

We have performed central BE computations and shocked one, after applications of the shocks given in Figure 1 above. We gather the results of these computations in the following tables in Figures 19 (asset allocation 1) and 20 (asset allocation 2). Number in parentheses provide the statistical errors associated with each computation of BE (defined as being the half 95% confidence interval around the relative error). Experiments 1, 2 and 3 have been run using the scenarios generated by, respectively, settings 1, 2 and 3 (described above); they have been run similarly for both asset allocations 1 and 2. Note that different experiments 1 yield the reference runs as they correspond to current standard computations. Experiment 4 below is not the same for both asset allocations. In this experiment, we have tried to magnify the impacts. That is why we have run asset allocation 1 with the setting 5 (in which we have divided by two the volatility of “the green index”) and run asset allocation 2 with setting 4 (in which we have doubled the volatility of “the brown index”).

FIGURE 19: BEST ESTIMATE AND TVFOG WITH ASSET ALLOCATION 1

EXPERIMENTS	CENTRAL BES	SHOCKED BES
#1	216 404 170.3 (± 0.484%)	211 306 676.4 (± 0.481%)
#2	214 506 348.4 (± 0.477%)	209 293 803.2 (± 0.474%)
#3	215 657 918.5 (± 0.502%)	210 580 811.9 (± 0.493%)
#4	215 985 470.5 (± 0.724%)	211 110 385.7 (± 0.714%)[6]
EXPERIMENTS	**CENTRAL TVFOGS**	**SHOCKED TVFOGS**
#1	31 924 277.5	26 826 783.6
#2	30 026 455.6	24 813 910.4
#3	31 178 025.7	26 100 919.1
#4	31 505 577.7	26 630 492.9

FIGURE 20: BEST ESTIMATE WITH ASSET ALLOCATION 2

EXPERIMENTS	CENTRAL BES	SHOCKED BES
#1	216 404 172.4 (± 0.484%)	207 627 224.9 (± 0.478%)
#2	214 016 758.8 (± 0.465%)	205 040 351.6 (± 0.463%)
#3	214 447 435.9 (± 0.474%)	205 669 377.9 (± 0.469%)
#4	216 702 826.1 (± 0.755%)[6]	207 942 084.9 (± 0.703%)[6]
EXPERIMENTS	**CENTRAL TVFOGS**	**SHOCKED TVFOGS**
#1	31 924 279.6	23 147 332.1
#2	29 536 866.0	20 560 458.8
#3	29 967 543.1	21 189 485.1
#4	32 222 933.3	23 462 192.1

[6] For computational constraints, experiment 4 has been run using 2,500 trajectories, explaining the increase of the statistical error.

We observe first that differentiating the modelling per sector (in terms of volatility structure and/or diversification through experiments 2 and 3) provides already non-neglectable impacts on BEs (up to 1%, depending on the configuration), when compared to the reference values of BEs obtained in experiment 1. However, applying the shocks does not seem to provide any further distinction.

Furthermore, we recover some expected behaviour:

1. Increasing the exposure to the brownest sector increases the impacts of the application of the shocks for both BEs and TVFOGs when compared to the central calculations; but again, the impacts of the shocks seem invariant with respect to the granularity of the modelling framework.
2. Decreasing the volatility of a green sector (as in experiment 4 in asset allocation 1) seems to slightly decrease the impacts of the shocks. In our experiment, we do not try to have a high exposure to the green sector, but it is reasonable to think that central BEs and shocked BEs would be even closer with high exposure to the green sector.

These results pave the way to possible further studies:

1. Applying instantaneous shocks on returns seems to have no further impact when compared to modifying the granularity of the modelling. It could be interesting to consider shocks on volatilities of each index.
2. Moreover, as transition risk may increase as time passes, it could be valuable to realise a similar study at a different time horizon, as in an own risk and solvency assessment (ORSA) calculation, in which different shocks on returns (and volatilities) are applied.
3. The whole volatility embedded in economic scenarios also depends on the correlation structure between sector index; the present study can be completed by performing some correlation sensitivities based on an historical analysis. The deformation of the correlation structure over time could be analysed (as has been done for volatility structure in Figure 6 above) to derive relevant sensitivities.

Conclusion

This paper describes in detail the simulation risk-neutral scenarios allowing us to integrate transition climate risk. The main issue is to parametrise with a sufficient granularity the modelling of equities included in the asset portfolio of the considered company. Our methodology relies on a hybrid of historical calibration along with market-consistency criterion. With a proper granularity of the modelling, shocks prescribed by EIOPA related to this transition risk can be applied and ALM impacts have been tested using these scenario.

CONTACT

Sophian Mehalla
sophian.mehalla@milliman.com

Grzegorz Darkiewicz
grzegorz.darkiewicz@milliman.com

Michal Krzeminski
michal.Krzeminski@milliman.com

Céline Francony
celine.francony@milliman.com

APPENDIX

A Fisher confidence interval

Recall that the correlation between sector I and J is denoted by $\rho_{I,J}$. The confidence interval around its estimation is calculated thanks to the Fisher transformation of the correlation $\rho_{I,J}$:

$$z_{I,J} = \frac{1}{2}\ln\left(\frac{1+\rho_{I,J}}{1-\rho_{I,J}}\right).$$

The bounds of the confidence interval around the Fisher transformation, at a threshold of 5%, are given by:

$$Z_{I,J}^{\pm} = z_{I,J} \pm \phi^{-1}(0{,}975) \times \sqrt{\frac{1}{N-3}},$$

where $\phi^{-1}(0{,}975)$ is the 97.5% quantile of the reduced centred normal distribution and $N = 256$ is the number of points employed for estimating the correlations.

To obtain the final confidence interval around the correlation estimation itself, we apply the inverse of the Fisher transformation to the bounds $Z_{I,J}^{+}$ and $Z_{I,J}^{-}$ to get:

$$IC_{I,J}^{\pm} = \frac{e^{2\times Z_{I,J}^{\pm}} - 1}{e^{2\times Z_{I,J}^{\pm}} + 1}.$$

REFERENCES

[IPPC] IPCC AR6 – Synthesis report of the IPCC sixth assessment report (March 2023), **HTTPS://REPORT.IPCC.CH/AR6SYR/PDF/IPCC_AR6_SYR_LONGERREPORT.PDF**

[ACPR] ACPR – Les principaux résultats de l'exercice pilote climatique 2020 – 2021. **HTTPS://ACPR.BANQUE-FRANCE.FR/SITES/DEFAULT/FILES/MEDIAS/DOCUMENTS/20210602_AS_EXERCICE_PILOTE.PDF**

[EIOPA] - EIOPA – Climate stress test for the occupational pensions sector 2022 (December 2022). **HTTPS://WWW.EIOPA.EUROPA.EU/BROWSE/FINANCIAL-STABILITY/OCCUPATIONAL-PENSIONS-STRESS-TEST/CLIMATE-STRESS-TEST-OCCUPATIONAL-PENSIONS-SECTOR-2022_EN**

[BoE] Bank of England – Results of the 2021 Climate Biennial Exploratory Scenario (May 2022). **HTTPS://WWW.BANKOFENGLAND.CO.UK/STRESS-TESTING/2022/RESULTS-OF-THE-2021-CLIMATE-BIENNIAL-EXPLORATORY-SCENARIO**

[FED] - FED – CRISK: Measuring the Climate Risk Exposure of the Financial System (September 2021). **HTTPS://WWW.NEWYORKFED.ORG/MEDIALIBRARY/MEDIA/RESEARCH/STAFF_REPORTS/SR977.PDF?SC_LANG=EN**

[LBGF] - Li, H., Bouri, E., Gupta, R., & Fang, L. (2023). Return volatility, correlation, and hedging of green and brown stocks: Is there a role for climate risk factors? *Journal of Cleaner Production*, 137594.

[Reports] – The various sources used:

Adyen (8 February 2023). Adyen publishes H2 2022 financial results Retrieved 17 December 2023 from **HTTPS://WWW.ADYEN.COM/PRESS-AND-MEDIA/ADYEN-PUBLISHES-H2-2022-FINANCIAL-RESULTS.**

Airbus (16 February 2023). FY Results 2022. –Retrieved 17 December 2023 from **HTTPS://WWW.AIRBUS.COM/SITES/G/FILES/JLCBTA136/FILES/2023-02/AIRBUS%20FY%202022%20RESULTS%20PRESENTATION_0.PDF.**

Air Liquide. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/AIR-LIQUIDE-4605/.**

Anheuser-Bush InBev SA/NV. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/ANHEUSER-BUSCH-INBEV-SA-N-31571356/SOCIETE/.**

ASML. Our Company. Retrieved 17 December 2023 from **HTTPS://WWW.ASML.COM/EN/INVESTORS/ANNUAL-REPORT/2022/HIGHLIGHTS#OUR-COMPANY.**

BASF SE. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/BASF-SE-6443227/SOCIETE/.**

Danone (April 2023). Integrated Annual Report 2022. –Retrieved 17 December 2023 from **HTTPS://WWW.DANONE.COM/CONTENT/DAM/CORP/GLOBAL/DANONECOM/RAI/2022/DANONE-INTEGRATED-ANNUAL-REPORT-2022.PDF.**

EssilorLuxottica. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/ESSILORLUXOTTICA-4641/SOCIETE/.**

Nokia OYJ. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/NOKIA-OYJ-56358470/SOCIETE/.**

Prosus N.V. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/PROSUS-N-V-66148584/.**

Safran. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/SAFRAN-4696/SOCIETE/.**

Sanofi. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/SANOFI-4698/SOCIETE/.**

SAP SE. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/SAP-SE-436555/SOCIETE/.**

Siemens AG. Zonebourse. Retrieved 17 December 2023 from **HTTPS ://WWW.ZONEBOURSE.COM/COURS/ACTION/SIEMENS-AG-56358595/SOCIETE/.**

TotalEnergies SE. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/TOTALENERGIES-SE-4717/SOCIETE/.**

Volkswagen AG. Zonebourse. Retrieved 17 December 2023 from **HTTPS://WWW.ZONEBOURSE.COM/COURS/ACTION/VOLKSWAGEN-AG-436737/SOCIETE/.**