Climate Risk Scenario Analysis for the Trading Book

Phase 2

Febuary 2024

Contents

Executive Summary

Climate scenario analysis has become a central focus for banks and financial institutions, especially as regulatory expectations have become more stringent, requiring firms to understand and assess both short-term and long-term financial risks associated with climate change. In recent months, there has been a heightened emphasis on recognizing and effectively managing the immediate impacts of climate-related financial risks on the business models of firms.

Measuring climate risk in the short term presents unique challenges for firms, particularly when evaluating the impact from a trading book perspective. This involves the consideration of severe and plausible climate risk scenarios within a horizon of less than one year. In the first half of 2023, ISDA commissioned Deloitte to develop a conceptual framework[1] and key issues to consider for the design and implementation of climate risk scenarios for the trading book, with the aim of producing a set of corresponding market risk factors consistent with climate risk as an output.

This framework was used as the basis for a pilot exercise to develop three short-term climate scenarios for the trading book. These comprise: a physical risk scenario that involves a sudden and dramatic increase in temperature; a transition risk scenario encompassing a sharp increase in carbon taxes; and a combined physical and transition risk scenario. All three scenarios entail falls in equity prices and rises in credit spreads across regions as economic growth slows in response to the climate shocks. Interest rates rise in the transition risk scenario as central banks battle rising inflation, but interest rates fall in the physical risk scenario as central banks focus on offsetting the shock to growth. Emerging market economies experience larger impacts on their economies and associated financial asset prices than advanced economies in all three scenarios. These scenarios are intended to support banks as they broaden their climate scenario analysis capabilities to include the trading book.

Some of the key factors that formed part of this exercise included:

- The exercise has produced a detailed set of scenario parameters covering a range of market risk factors in the three scenarios, including country and sector specific parameters. Given the exercise was a pilot, coverage of the scenarios is partial and should be expanded in future work.
- The geographical areas covered in this pilot exercise were divided into developed markets (the EU, Japan, the UK and the US) and emerging markets, with Brazil and India selected as representative regions.
- An integral part of this exercise was a crowdsourcing exercise, which involved soliciting input from an ISDA working group on the magnitude and direction of the shocks. This process aimed to ensure that the shocks remained plausible for the trading book in the short term and is consistent with the role that subject matter experts typically play in most scenario analysis exercises.
- To support the crowdsourcing part of the exercise, the ISDA working group was provided with an initial set of model-based scenarios to discuss. A specific set of models was adopted for this exercise, but the group discussed how a range of different approaches could also have been used.
- The calibrated market risk shocks from the crowdsourcing exercise were used to assess the impact of the three scenarios on a set of hypothetical instruments based broadly on exercises that the European Banking Authority (EBA)[2] has conducted for benchmarking.
- The results were compared against various climate and regulatory exercises to provide a benchmark for the results of this pilot exercise.

The conceptual framework served as a crucial reference for conducting the climate scenario analysis in the trading book discussed in this paper. This process demonstrated the usefulness of each stage and key element delineated in the conceptual framework for the successful execution of climate scenario analysis within the trading book. Specifically, it was instrumental in evaluating the influence of climate-related risks on market risk factors.

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[1] www.isda.org/2023/07/12/a-conceptual-framework-for-climate-scenario-analysis-in-the-trading-book/

[2] www.eba.europa.eu/publications-and-media/press-releases/eba-publishes-annual-assessment-banks-internal-approaches

1. Introduction

1.1. Background and Objectives of Phase 2

Background

Between February and June 2023, over 30 banks were engaged to define a conceptual framework for climate scenario analysis in the trading book. This was in response to feedback from the industry for support in developing short-term scenarios that are designed for the trading book. Up until that point, the primary focus of climate scenario analysis had been on longer-term scenarios, targeted on the banking book. This research sought to determine how physical and transition risks translate into the relevant market risk shocks for the trading book.

As part of this phase (Phase 1), a survey was launched to explore banks' current practices and future expectations. The responses were used to develop a conceptual framework on how to approach climate scenario analysis for the trading book, leveraging the survey findings, working group discussions and bilateral meetings with the banks. The paper[3] summarized the industry's current practices and future goals and included key considerations for a conceptual framework and its underlying principles.

Objectives of Phase 2

In the second half of 2023, there was a desire from the ISDA working group to test the conceptual framework designed in Phase 1. ISDA commissioned Deloitte to support the design and modelling of three climate scenarios for the trading book. These comprised a physical risk scenario, a transition risk scenario and a combined scenario, which involves both physical and transition risk events occurring concurrently. These scenarios were designed to be consistent with longer-term scenarios but capture the potential severity of climate events in the short term. This was achieved by calibrating transition and physical risk shocks that are consistent with longer-term climate risk scenarios and implementing them as one-off, permanent shocks at the beginning of the scenarios (instead of assuming they occur gradually over many years).

A key differentiator of this exercise is that scenario analysis for the trading book focuses primarily on a scenario horizon up to one year, whereas other short-term scenarios are more aligned to the banking book with scenario horizons between three and five years. Until now, the industry's focus has been to design scenarios to explore the impact of climate events on macroeconomic variables and the broader economy. This exercise was intended to produce scenarios that translate climate shocks into macroeconomic variables, which then propagate into market risk factor shocks.

The working group agreed on the calibration of the scenario variables through a crowdsourcing exercise, using a set of modelled macroeconomic outputs and market risk shocks as a starting point. The purpose was to deliver a set of shocks that are severe yet plausible for the trading book. The calibrated market risk shocks were then applied to a set of hypothetical instruments to generate illustrative impacts of climate risk on the trading book.

[3] www.isda.org/2023/07/12/a-conceptual-framework-for-climate-scenario-analysis-in-the-trading-book/

2. Alignment of Modelling Approach with the Conceptual Framework

The purpose of this exercise was to test the conceptual framework developed in Phase 1 (see Figure 1). This framework supports the design and implementation of climate risk scenarios for the trading book through explicit consideration of climate risk factors, producing a set of corresponding market risk factors consistent with climate risk scenarios. The conceptual framework is set out in stages 1 to 5, with each stage underpinned by a set of key considerations that have been informed by the industry survey and working group insights.

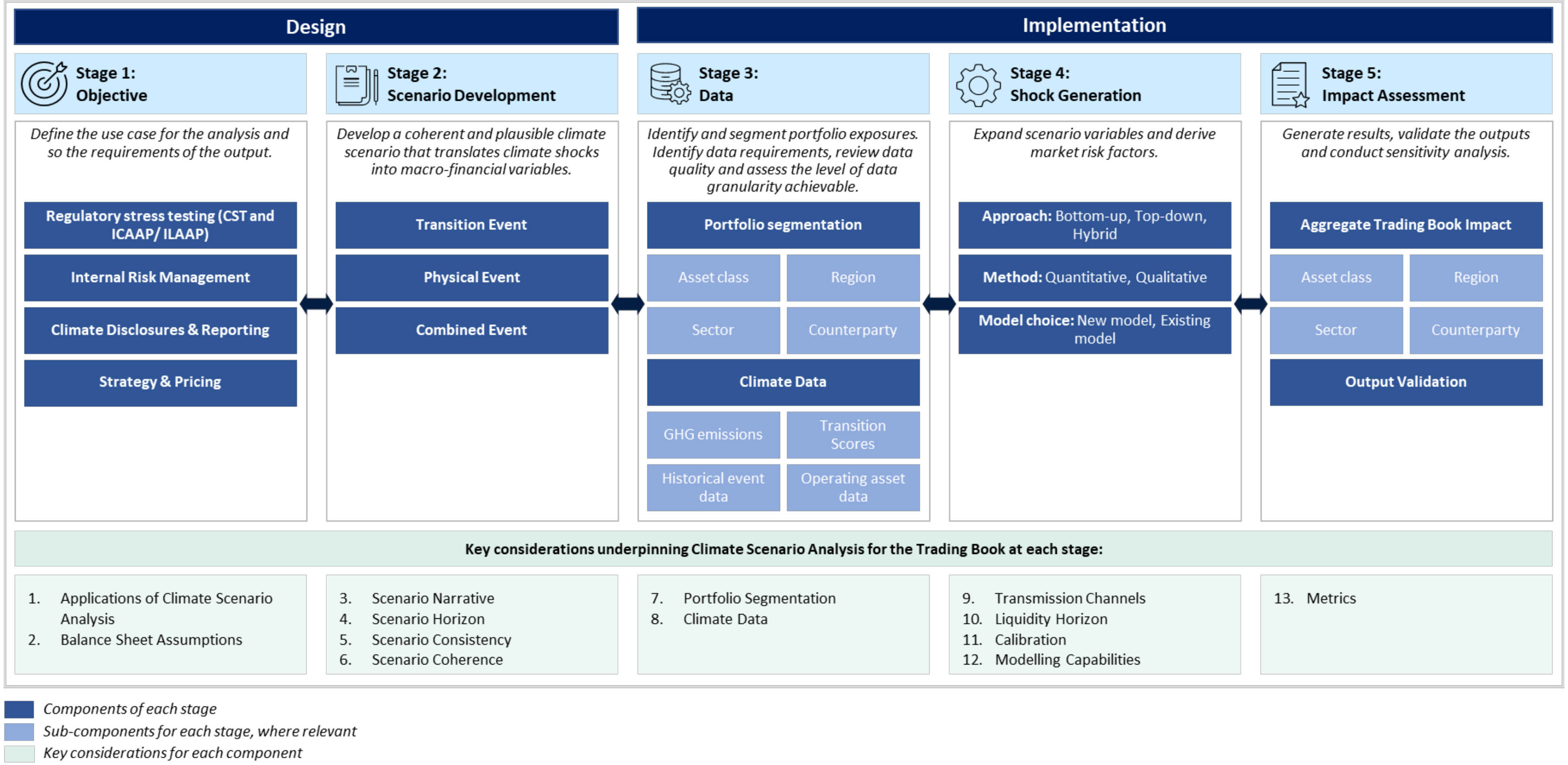

Figure 1: End-to-end Conceptual Framework for Climate Scenario Analysis in the Trading Book

Figure 2 overlays the conceptual framework with an illustration of the practical implementation steps to derive climate scenarios for the trading book, climate-adjusted macro financial variables and market risk factors. In Stage 1, the objective of the exercise was agreed to produce a pilot climate scenario analysis using the conceptual framework. In Stage 2, the decision was made to focus on three climate scenarios: a transition risk scenario; a physical risk scenario; and a combined scenario. In Stage 3, the sectors and regions were agreed, as well as the climate data that would be used and stressed in the scenarios. In Stage 4, shocks were produced using a combination of three models: a climate model; an agent-based macroeconomic model; and a set of market-risk expansion models. In Stage 5, the market risk factors were applied to a set of hypothetical instruments to produce estimates of the potential impacts of the climate scenarios. Each of the five stages is covered in further detail in the next section.

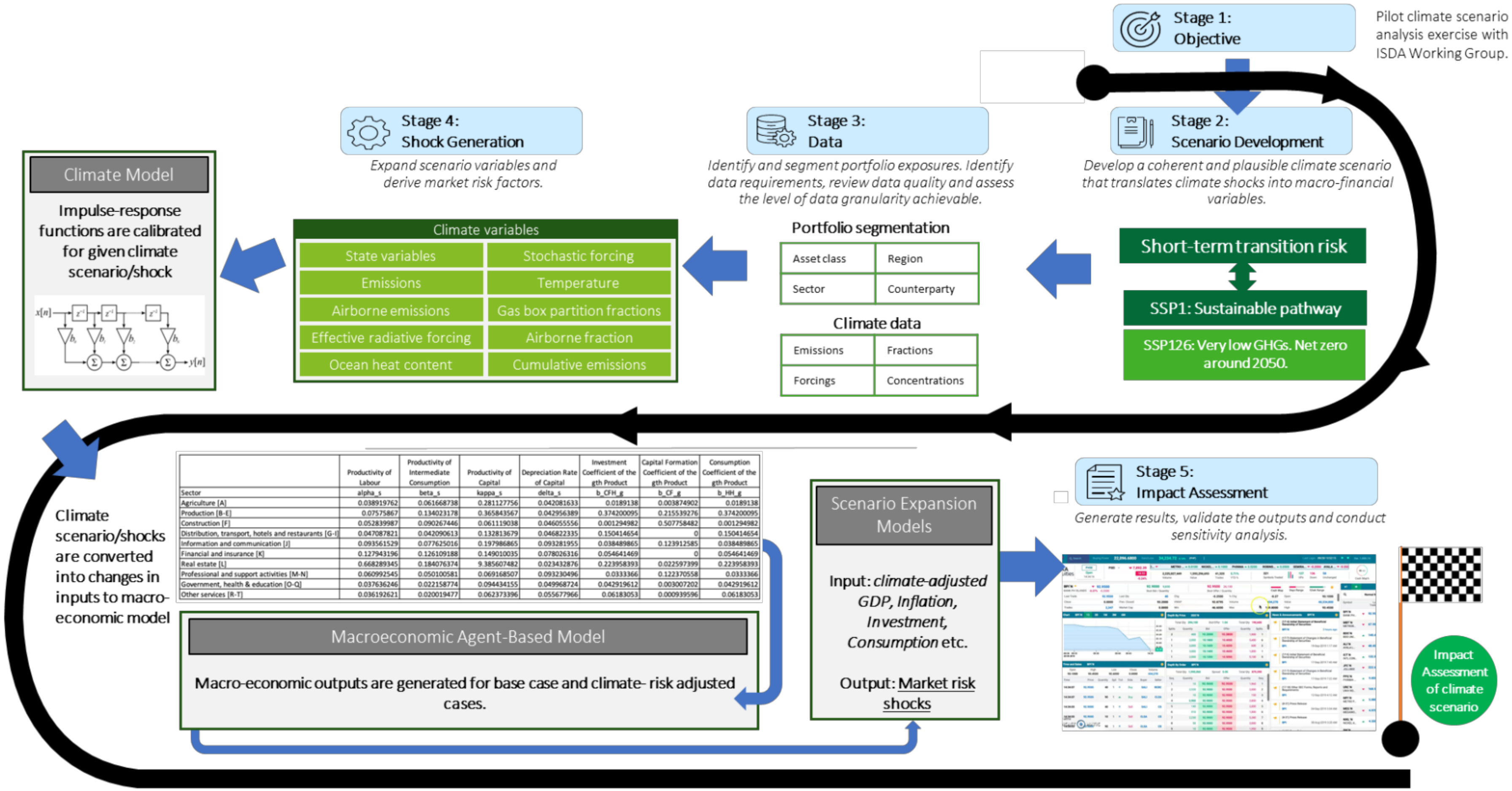

Figure 2: Alignment to the Conceptual Framework

3. Detailed Modelling Approach and Alignment with Conceptual Framework

3.1. Stage 1: Objective

As a first stage of any climate scenario analysis, it is important to establish the use case. Some examples of use cases for climate scenario analysis include climate stress tests mandated by regulators, internal risk management practices, climate-related disclosures and informing strategy and business decision making.

The objectives of this exercise are to provide a pilot of the conceptual framework, develop three climate scenarios tailored for stress testing for the trading book and provide an impact assessment of the climate risk scenarios on the trading book. By doing so, banks can evaluate the impact of climate conditions on market risk factors, thereby assessing the resulting effects on their trading book portfolios and overall financial performance. These scenarios can be utilized by organizations in their internal risk management procedures, supporting them in establishing their climate risk appetite and informing hedging strategies in the future. The exercise also allows the working group to evaluate and adjust the conceptual framework published in July 2023.

Unlike prevailing scenarios that primarily concentrate on assessing the impact of climate on macroeconomic variables over long horizons, this exercise focuses on translating climate-related shocks into market risk factors shocks over short horizons. Shorter-term scenarios currently in development typically span a horizon of three to five years and are primarily applicable to the banking book. To develop climate scenarios more pertinent for the trading book, a horizon of up to one year is more appropriate to capture the severity of shocks in the near term. These adjustments are necessary to achieve the primary objective of developing severe yet plausible scenarios for the trading book.

3.2. Stage 2: Scenario Development

The ISDA working group has reviewed various existing longer-term scenarios (eg, those by the European Central Bank (ECB), the Intergovernmental Panel on Climate Change (IPCC) and the Climate Biennial Exploratory Scenario) to determine which scenarios are most appropriate to utilize as a baseline for the trading book. The IPCC Shared Socioeconomic Pathways (SSP) scenarios were found to be most widely used by the industry. The SSP245 ('middle of the road') scenario was selected as the baseline, as it corresponds to emissions pathways based on current global trends in which social, economic and technological trends do not shift markedly from historical patterns.

To account for the severity of climate shocks adequately in the short term, a set of transition and physical risk shocks had to be calibrated. Following guidance from the conceptual framework, these calibrations were informed by those used in existing longer-term scenarios. The ECB's disorderly transition scenario was used as a reference point to inform the transition risk short-term scenario and the Network for Central Banks and Supervisors for Greening the Financial System (NGFS) 'hot house world' was used as the basis for informing the physical risk scenario.

3.2.1. Scenario Narratives

Physical Risk Scenario

This scenario is characterized by a sudden deterioration in the physical risk environment caused by an acceleration of emissions into the atmosphere across the globe, resulting in an instantaneous increase in average global surface temperature of 1.5-degree Celsius above global average temperatures of between 1.2-

1.4-degree Celsius in 2023[4]. This is driven by an abrupt thawing of arctic permafrost[5] and a subsequent release of emissions.

The increase in emissions gives rise to a deterioration in the physical environment – for example, changes in precipitation, an increase in temperatures and a rise in sea levels. There is a material reduction in demand and an increase in savings among households in the face of this severe shock. Household consumption, government consumption and investment drop in line with declining output, and inflation falls. This is a phase-shift in the global climate, in which historical correlations no longer fully describe observed patterns of behavior.

The decline in GDP leads to reduced corporate profits and consumer spending, negatively affecting equity prices and overall indices. Equity sectors respond differently, depending on each sector's ability to remain resilient. In the economic slowdown, investors flock to the perceived safety of gold (increasing prices) and government bonds (putting downward pressure on yields). Emerging markets are more adversely affected by the global economic downturn, resulting in a currency depreciation in these regions.

Transition Risk Scenario

This scenario entails a sudden and dramatic increase in the price of carbon, implemented via a carbon tax. This follows the simultaneous acknowledgement by governments around the world that unless they act immediately and decisively, they will be unable to avoid the extremely undesirable consequences of not meeting the Paris Agreement goals. This represents an aggressive and challenging pathway to meet those commitments and aligns to the ECB's short-term disorderly scenario[6].

Coordinated action by multiple countries results in a simultaneous and instantaneous increase in the carbon price to $200 per ton via a carbon tax on production. Firms in high-polluting sectors are penalized to a greater extent than lower-emitting firms, according to the carbon intensity for each sector[7]. The carbon tax is assumed to be imposed as a tax on firm production and so the effect of the carbon tax is captured as a wedge between producer prices and consumer prices, with consumer prices rising while raw materials prices remain stable.

As the instantaneous additional tax is imposed on firm production, unit input costs increase, which is passed on to the consumer, fueling inflation. At the same time, output falls due to reduced demand for goods from highly polluting sectors. In response to higher observed inflation, all market participants forecast further increases.

Credit spreads widen as higher prices signal greater risk aversion by investors, which demand higher yields to compensate for a perceived increase in credit risk. The central bank for each country raises interest rates based on higher expected inflation (only partially offset by lower future economic growth), causing government bond yields to increase across all regions. Gold prices rise following flight-to-safety flows, but other commodity prices (eg, oil and coal) decline due to the overall impact of lower demand and the impact of the carbon tax. Emerging markets are more adversely affected by the global economic downturn, resulting in a currency depreciation in these regions.

Combined Scenario

This scenario mixes the heightened physical risks seen in the physical risk scenario with accelerated policy action in the transition risk scenario, resulting in a combined transition and physical risk stress. In this scenario, a sudden rise in temperature and associated physical risk stresses (ie, changes in precipitation, an increase in

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[4] www.climate.gov/news-features/understanding-climate/climate-change-global-temperature#:~:text=2023%20was%20the%20warmest%20year,average%20(1850%2D1900)

[5] www.unfccc.int/sites/default/files/resource/Permafrost%20v3.pdf

[6] www.ecb.europa.eu/pub/economic-bulletin/focus/2023/html/ecb.ebbox202302_06~0e721fa2e8.en.html#:~:text=In%20addition%2C%20the%20stress%20test,carbon%20prices%20over%20a%20short%2D

[7] *Air Emissions Intensities by NACE Rev. 2 Activity*. Eurostat, https://ec.europa.eu/eurostat/databrowser/view/env_ac_aeint_r2__custom_9357731/default/table?lang=en Accessed January 15, 2024

temperatures and a rise in sea levels) act as the trigger for government action to raise carbon taxes. The combined shocks lead to a downturn in the economy.

This leads to lower output and productivity across countries. Reduced productive capacity shrinks demand for intermediate goods, cutting aggregate demand and GDP across the world. Simultaneously, firms are hit with the additional carbon tax on production, leading to higher inflation as firms raise prices in response to increases in their cost base. Households cut back expenditure in anticipation of economic stress, compounded by a reduction in wages that materializes when firms seek to reduce costs, causing GDP to fall further.

The physical and transition risk shocks lead to equity prices falling and credit spreads to widen across countries as firm profits reduce. Policy interest rates and yield curves decline across most regions as the negative impacts on GDP from the transition and physical risk shocks outweigh the inflationary effects of the carbon tax shock. Commodity prices (eg, oil and coal) fall significantly due to the aggregated effects of lower global demand and the carbon tax. In the economic slowdown, investors flock to the perceived safety of gold. Emerging markets are hit harder by the global economic downturn, resulting in a currency depreciation in these regions.

3.3.Stage 3: Data

A key element of the conceptual framework was to identify the data to be used in the exercise. It is particularly important to identify the assets that institutions are most interested in exploring or think will be most vulnerable to climate risk. In terms of transition risks, this will typically mean focusing on sectors that may be exposed to climate transition policies to a greater or lesser extent, depending on their carbon intensity. For physical risks, this will involve focusing on economic factors that are more likely to be affected by acute and chronic physical risks as they emerge.

For this exercise, consideration was given to the data that would be used in terms of portfolio segmentation – which sectors, regions and assets – and the data required for modelling. Given this exercise is a pilot covering a range of globally active banks, the choice of regions, sectors and assets was selective.

Portfolio Segmentation

The conceptual framework emphasizes the significance of integrating portfolio segmentation into climate scenario analysis within the trading book. This initial exercise included segmentation based on geography, sector and asset class, with the aim of offering more detailed insights into how climate impacts the trading book. Figure 3 shows the geographical areas covered in this pilot exercise and is divided between developed and emerging markets.

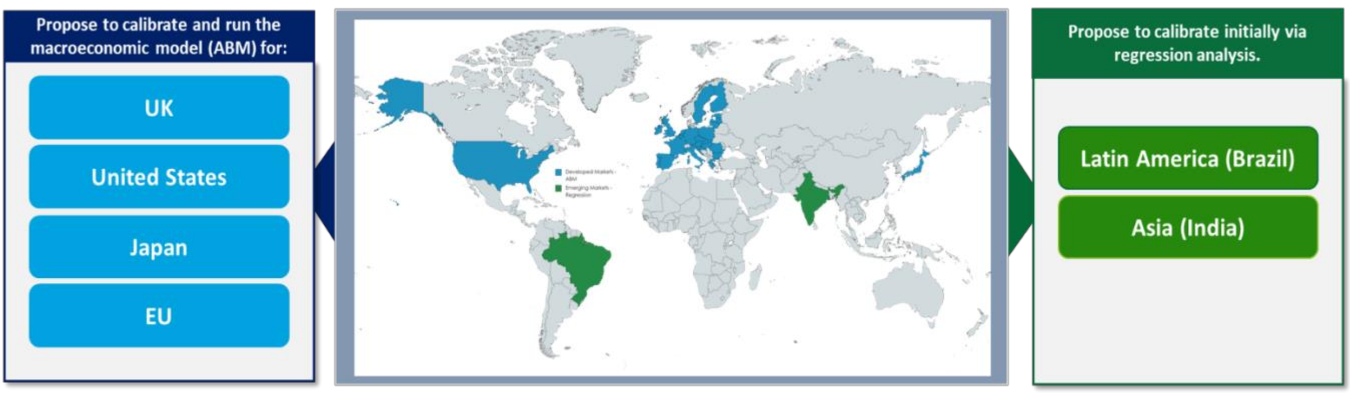


Figure 3: Geographical Coverage for the Climate Scenario Analysis

Collectively these regions cover 54% of the world's economy by GDP[8] and include the major trading regions that the working group wanted to consider in terms of transition policy risks and the losses associated with physical risk hazard events. The two emerging market regions are expected to have heightened exposure to the

[8] www.imf.org/external/datamapper/PPPSH@WEO/EU/CHN/USA

physical risk shock. The emerging market shocks are applied as exogenous events that feed into the market risk scenario expansion by adjusting the inputs for the developed countries.

The EU was chosen for granular sectoral-level modelling in order to conduct a more detailed assessment of climate impacts – particularly transition-based climate effects. The chosen sectors for this analysis include air transport, land transport, electricity, mining and quarrying, manufacturing of chemical products and publishing activities. These were selected with the aim of capturing the impact on the most carbon-intensive sectors. The inclusion of the publishing sector for equities, known for its lower carbon footprint, served as a control, enabling the working group to assess and compare the climate-specific impact. With insights gathered from the industry, and leveraging existing stress testing exercises as a reference, a list of asset classes and macro risk factors was compiled for this exercise. A description of the data models for each region can be found in Appendix B.

3.4. Stage 4: Shock Generation

A key input into the working group's crowdsourcing discussion was an initial set of macroeconomic and market risk shocks generated by a series of quantitative models, described in this section. These can be categorized as a climate model, a macroeconomic model and a series of scenario expansion models that convert macroeconomic shocks to market risk factors over a one-year horizon. A more detailed description of the modelling methodology is available in the Appendix B.

Figure 4 provides a high-level example of the end-to-end process for translating climate risk factors into climate-adjusted macro and market risk factors. The purpose of this illustration is to describe the process for modelling a single market risk factor – in this case, climate-adjusted UK yield curves – in response to a physical risk shock. However, similar processes are followed for other market risk factors.

For the physical risk shock, an instantaneous 1.5-degree Celsius temperature rise is fed into the macroeconomic model. This runs in a monthly timestep to produce a set of climate macroeconomic pathways for macro factors, such as GDP, inflation and central bank policy rates for each region[9]. These factors are modelled at each monthly timestep and used as an input to the relevant market risk model – in this case, a one-factor Hull-White model. Using the appropriate historical data, the yield curves are calibrated for each timestep in the specific region. The first simulation point is one day following the reference date of the simulation – June 30, 2023. Therefore, every subsequent timestep refers to one day plus a number of months.

The process is repeated for each region and the relevant market risk model is applied to generate the factors for the various asset classes.

[9] An interpolation method is used where market risk shocks fall between two simulated timesteps.

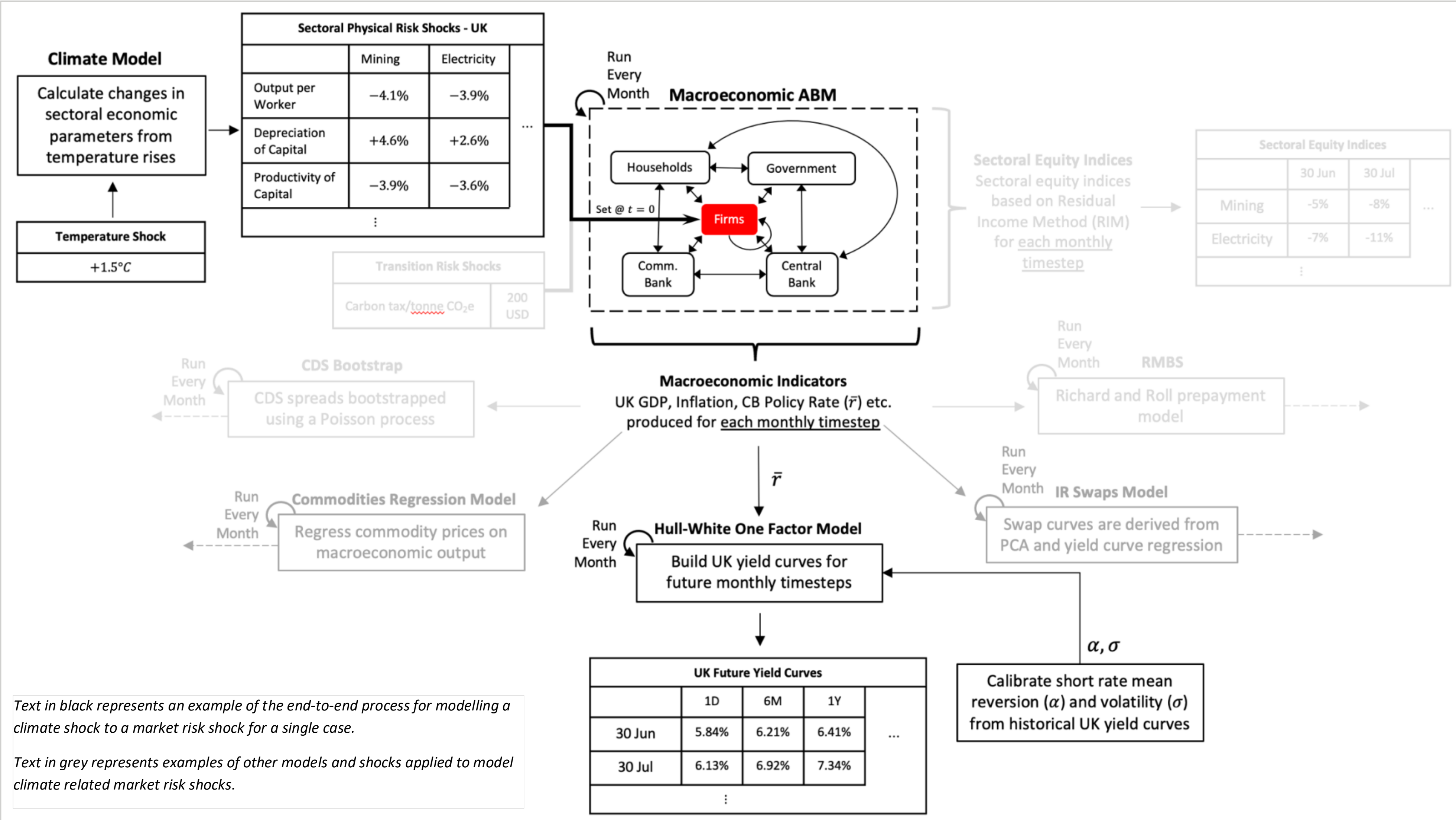


Figure 4: End-to-end Illustration of the Process for Calculating Climate-adjusted Macro and Market Risk Factors for the Trading Book

A single case is highlighted for brevity: physical risk shocks on yield curves for the UK economy. Note that all numbers shown are for illustrative purposes only.

3.4.1. Climate Model

The first key modelling block is the climate model. This translates climate shocks expressed in terms of typical climate variables, such as temperature, radiative forcing and carbon dioxide, into a set of variables that can be used as inputs into a macroeconomic model. The set of shocks produced by the climate model includes labor productivity and depreciation. These shocks are produced at a sectoral level, generating a much richer set of climate impacts than if aggregate country impacts were used. A standalone climate model is essential to determine the impact of a phase shift in the global climate and economy, where historical correlations may no longer fully describe the observed behavior. This is explained in detail in Appendix B.

3.4.2. Carbon Tax Pathway

The shock from the transition scenario is also applied from the first step in macroeconomic model simulation. Emission intensities for different economic sectors[10] (tons CO2e per million unit of local currency output) are multiplied by the prescribed carbon tax ($200/ton CO2e) to derive an implied tax on production. This is added to the existing tax on production for each sector, which is calculated from national accounting identities following the methodology of Poledna et al (2020)[11]. This imposes extra costs on firms in highly polluting sectors, reducing profits and causing shocks to propagate bidirectionally through firm supply chains.

3.4.3. Macro Model: The Agent-Based Model

The second key modelling block is the macroeconomic model. This model takes a set of climate-adjusted shocks from the climate model as inputs and processes them to produce a set of macroeconomic pathways. For this pilot exercise, an ABM was used. The macroeconomic ABM prescribes a set of heterogeneous agents that interact, trade and adapt their behavior to current and expected conditions in the economy. By modelling the interactions of market participants from the bottom up, the complex and non-linear dynamics of real economies can be captured.

This is especially important for modelling emergent behavior associated with climate change, which has no historical precedent to calibrate traditional top-down models, like those based on general equilibria. The diversity of agents within the model also allows for greater sectoral granularity, which helps to understand how different parts of the economy will be affected by physical and transition risks. An ABM like the one employed for this exercise has been successfully used to model various economic crises in the euro area. In a paper on this topic, the authors show that the model is capable of predicting turmoil arising endogenously during the period following the 2008/2009 financial crisis without any exogenous shocks. It was also used to predict the inflationary dynamics of the economic recovery following the COVID-19 pandemic.

The ABM model is based on a paper entitled *Economic Forecasting with an Agent-based Model* by Polenda et al (2019)[12]. As described in this paper, an ABM is developed to fit the macroeconomic data of an open economy that forecasts variables such as GDP (including its components), inflation and interest rates. Markets are fully decentralized and characterized by a continuous search-and-matching process, which allows for trade frictions. The ABM allows the assumption of rational expectations from equilibria-based economic models to be relaxed. Here, agents' expectations are formed through bounded rationality, which provides a less restrictive representation of behavior. Agents also learn from and adapt to prolonged adverse shocks. For example, the

[10] *Air Emissions Intensities by NACE Rev. 2 Activity*. Eurostat, https://ec.europa.eu/eurostat/databrowser/view/env_ac_aeint_r2__custom_9357731/default/table?lang=en . Accessed January 15, 2024

[11] Hommes, Cars H. and Poledna, Sebastian, Analyzing and Forecasting Economic Crises with An Agent-based Model of the Euro Area, March 7, 2023, https://ssrn.com/abstract=4381261 or http://dx.doi.org/10.2139/ssrn.4381261

[12] Poledna, Sebastian, et al, Economic Forecasting with an Agent-based Model, 3484768, February 24, 2020, https://doi.org/10.2139/ssrn.3484768.

autoregressive models that govern expectations of inflation and economic growth are recalibrated at each time-step based on the latest data generated by the model.

The key to incorporating transition climate risk into traditional macroeconomic variables is to include the trajectory for sectoral carbon emissions. The carbon tax propagates through the model via price channels, raising inflation rates and factoring into central banks' policy reactions. Heavily polluting sectors will therefore experience higher costs than less polluting ones. The emissions intensities remain constant throughout the ABM simulation, assuming firms do not have time to adjust their processes to reduce emissions in line with the timescale of a typical trading book scenario.

To capture the impact of physical climate risk in the economy, the effects of changing temperature are also incorporated into the model. A sudden heat shock alters macroeconomic variables on a sector-by-sector basis, changing the dynamics of supply and demand across the economy. For example, the productivity of labor in the agricultural sector will generally decrease in response to higher temperatures. These shocks propagate throughout the economy while it finds a new equilibrium.

The ABM comprises the following agents: firms, households, government, banks and central banks. The number of each type of agent is set according to business demography and census data, as described in the appendix. These are the five domestic agents that interact with the rest of the world through imports and exports.

3.4.4. Market Risk Shocks

A crucial part of the conceptual framework is translating the climate-adjusted macroeconomic shocks into market risk shocks. For this pilot exercise a range of expansion models were used to develop market risk factors for each asset class. The suite of models used should be viewed as illustrative and is intended to be a useful starting point for individual institutions to build from. A mapping of models to market risk factors is provided in Table 1.

The detailed methodology and equations for each of the models can be found in Appendix B.

Market Risk Factor	**Model**
Nikkei225	Fama French 5 Factor Model
Sectoral Equity Indices (EU)	Residual Income Method
S&P 500	Fama French 5 Factor Model
FTSE 100	Fama French 5 Factor Model
Sectoral Credit (EU)	Merton LSTM
USD 5Y Credit Default Swap (CDS) on UK	Merton LSTM
Government Yield Curves	Hull White One Factor Model
Interest Rate Swap Curves	PCA Component Regression
FX	XGBoost Regressor – GBP Purchasing Power Parity
Commodities	Regression on ABM Macroeconomic Outputs
US Residential Mortgage-backed Securities (RMBS)	Richard & Roll Prepayment Model

Table 1: Mapping of Market Risk Factors to Models

3.5. Stage 5: Results and Impact Assessment

This section sets out the results from the methodology described in the previous segment to produce climate-adjusted macroeconomic and market risk factor shocks for the three climate scenarios (physical risk, transition risk and a combined scenario) over a one-year horizon. The macro results are described first, because they drive the impact to the market risk factors that are most important for the trading book.

3.5.1. Macro Results

The macro model uses a set of climate-adjusted shocks from the climate model as inputs and processes them to produce a set of macroeconomic pathways over a one-year horizon.

GDP & Inflation

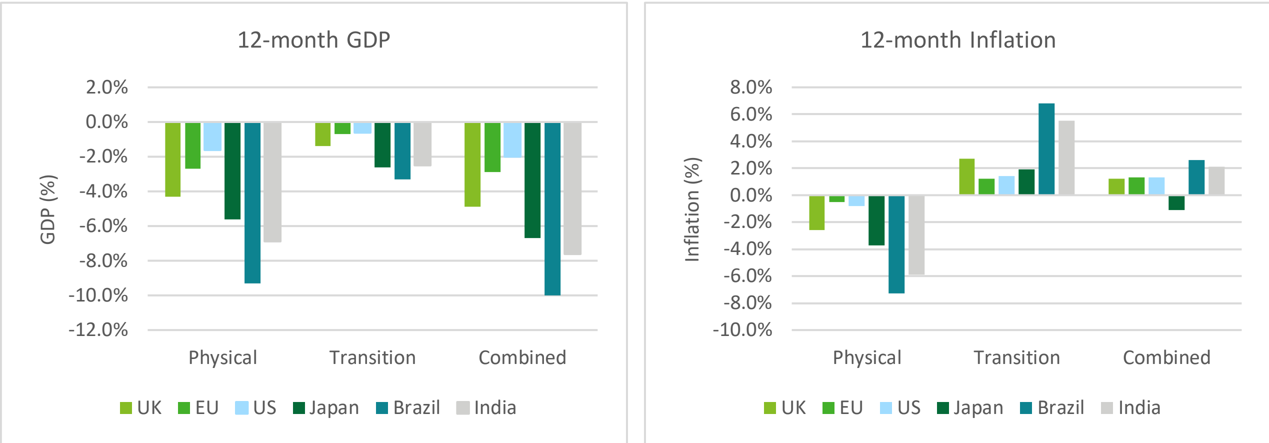
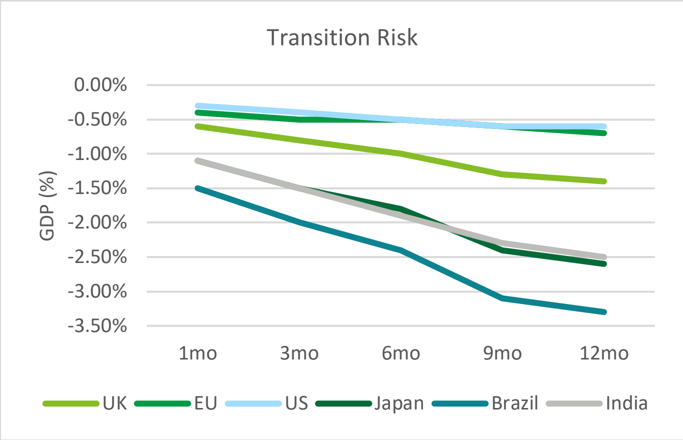


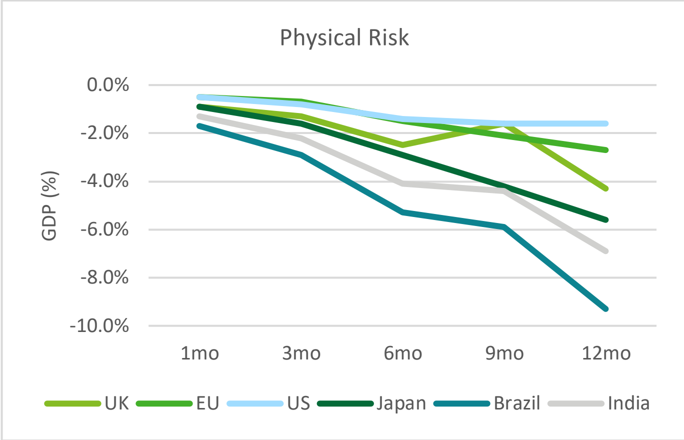
Figure 5: 12-month GDP and Inflation Across Regions

GDP declines across all the regions for the physical risk, transition risk and combined scenarios (Figure 5, 12-month GDP). The decrease in GDP for the physical risk scenario is more pronounced compared to the transition risk scenarios, reflecting the large size of the temperature shock imposed at the start of the scenario. The 1.5-degree Celsius temperature shock has been calibrated based on the difference between the NGFS 'hot house world' and the 'middle of the road' scenarios as at the end of the century but has been imposed at the start of the scenario and is therefore a very significant shock. Particularly large impacts would occur for Japan, as manufacturing makes up a greater portion of the Japanese economy and this sector is more severely affected by physical risk and transition risk events. The emerging market economies are severely affected in all three scenarios, consistent with the historical tendency for their GDP to be more volatile and their economies to be more vulnerable to large economic shocks.

Inflation rises in all regions in the transition scenario, due to the imposition of a carbon tax and the associated increase in input costs and prices (Figure 5, 12-month Inflation). The physical risk scenario entails a drop in inflation in all regions, consistent with the large declines in GDP. Those regions that experience the largest falls in GDP, such as Japan, India and Brazil, also see the largest reductions in inflation.

In the combined scenario, inflation is somewhat higher in most regions, as the inflationary impacts of the carbon tax shock outweigh the negative effects from lower GDP from the physical risk shock. In Japan, inflation falls a little, as the particularly large negative effects on GDP from the physical risk scenario are sufficient to outweigh the inflationary impacts of the carbon tax. Figure 6 plots the macroeconomic trends for GDP over the one-year scenario horizon for physical risk, transition risk and combined scenarios, illustrating how GDP performs over time as the different climate risks propagate through the economy.





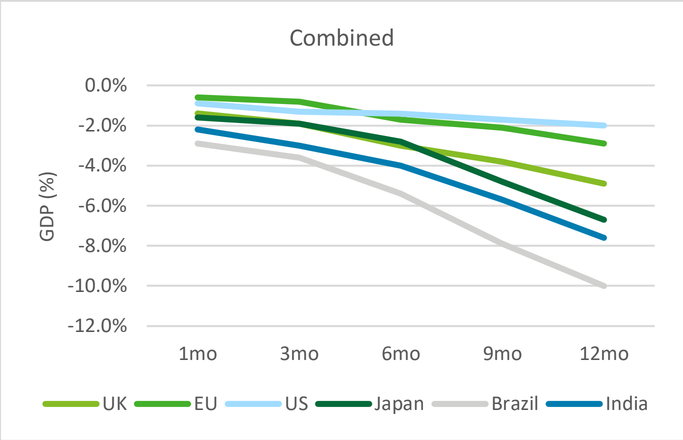


Figure 6: GDP Performance Under the Physical Risk, Transition Risk and Combined Scenario Over Scenario Horizon

Note that values shown are with respect to the baseline scenario[13].

GDP declines across all regions for the physical risk, transition risk and combined scenario. Across all three scenarios, the impacts increase through time. In the transition risk scenario, however, the effect shows signs of flattening out at the nine-month point as the economy begins to adjust to the new equilibrium with higher carbon taxes. GDP for physical risk shows less evidence of flattening out, consistent with the economy taking longer to adjust to the particular large shock.

3.5.2. Market Risk Results and Crowdsourcing

This section details the market risk results after the climate-adjusted macroeconomic shocks are translated into market risk shocks through a range of expansion models summarised in section 3.4.4 and described in detail in Appendix B. The market risk shocks were modelled for four different liquidity horizons to capture the relevant horizons for the various asset classes. Following consultation with the ISDA working group, shocks were generated for one-day, 10-day, three-month, and one-year liquidity horizons.

After the production of market risk shocks, a series of calibration exercises was conducted through crowdsourcing within the working group. The objective was to solicit input from the working group on the magnitude and direction of the shocks. This process aimed to ensure that the shocks remained plausible for the trading book in the short term and is consistent with the role that subject matter experts typically play in most scenario analysis exercises. The working group received a template containing market risk shocks for three scenarios and was tasked with specifying their expected shock values and directions for each market risk factor

[13] Note that values shown are with respect to the baseline scenario.

associated with the given liquidity horizon. In providing expected values, the working group drew on a variety of sources, including internal scenario analysis, historical timeseries and input from internal subject matter experts.

The working group contributed insights on macroeconomic and market risk shocks across six regions. While most of the feedback from individual participating banks was qualitative, a few provided explicit quantitative feedback on the desired shock size and direction.

Emphasis within the working group was primarily on the one-day and 10-day horizons, as these were deemed the most relevant for their trading book exposures. This was also where the greatest amount of feedback was received. Calibration of the market risk shocks incorporated the feedback received from the working group, with adjustments made to ensure that the relationships between the shocks remained intuitive. The following section presents the outcomes of the crowdsourcing exercise, detailing results for each asset class across different liquidity horizons for each scenario.

Equities

Asset Class	Region	Sector	Risk Factor	ISDA Proposed Shocks											
				Transition Risk				Physical Risk				Combined			
				1D	10D	3M	1Y	1D	10D	3M	1Y	1D	10D	3M	1Y
Equities (percentage change)	Asia		NIKKEI 225	-5%	-10%	-15%	-20%	-5%	-10%	-20%	-25%	-5%	-10%	-20%	-20%
	Europe	Air Transport		-10%	-20%	-25%	-30%	-5%	-10%	-15%	-20%	-10%	-20%	-25%	-20%
		Electricity		-10%	-20%	-25%	-30%	5%	5%	10%	15%	5%	5%	10%	15%
		Mining & Quarrying		-15%	-25%	-30%	-35%	0%	0%	0%	0%	-15%	-25%	-30%	-35%
		Publishing Activities		0%	-5%	-10%	-10%	0%	0%	0%	5%	0%	-5%	-10%	-10%
		Manufacture Chem/Chem Prods		-10%	-20%	-25%	-30%	5%	10%	15%	20%	10%	10%	15%	20%
		Land Transport		-10%	-20%	-25%	-30%	-5%	-10%	-15%	-20%	-10%	-20%	-25%	-30%
	US		S&P 500	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%
	UK		FTSE100	-5%	-10%	-10%	-20%	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%

Table 2: Equity Market Risk Shocks

Transition Risk: There are substantial declines in equity prices across all indices and sectors in the transition risk scenario. The Nikkei 225, FTSE 100 and S&P 500 all see reductions of up to 20% at one year. This reflects the macroeconomic impacts of the carbon tax lowering GDP, while also pushing up inflation and interest rates, leading to reduced profits and valuations.

The effects are particularly pronounced for the EU carbon-intensive sectors selected by the ISDA working group for this exercise (air transport, electricity, mining and quarrying, manufacturing of chemicals and land transport). These sectors are particularly vulnerable to the carbon tax shock and experience large equity price declines between 10% and 35%. The mining and quarrying sector suffers the largest drop of 35% at one year. The working group selected publishing activities – deemed a low-carbon sector – as a control to assess shock sensitivity. The input costs associated with this sector are not heavily affected by the carbon tax, and this sector experienced a 0% to 10% decline in equity prices, depending on the liquidity horizon.

Physical Risk: There are also substantial declines in equity prices across indices in the physical risk scenario. Significant and enduring shocks to GDP occur in the UK, US and Japan, signaling reduced economic output and production, which leads to lower corporate earnings, negatively affecting equity prices. The FTSE 100 and S&P

500 experience falls of up to 20% at one year. The Nikkei 225 undergoes a larger decline of 25% at one year, consistent with the greater impact on GDP described in the macroeconomic effects section.

There is a more mixed picture for equity prices in the EU sectors. This is unsurprising given they were selected because of their vulnerability to transition risk (ie, carbon taxes) rather than their vulnerability to physical risk. Sectors with little climate exposure in their supply chain (eg, publishing activities) experience a negligible impact on equity values in response to the physical risk shock. There is a significant decline in equity prices for air and land transport, consistent with reduced travel demand observed during previous economic downturns and the physical risk narrative in which severe physical risk events damage destination areas and infrastructure. Conversely, sectors with less demand elasticity, such as electricity and manufacturing, experience an increase in equity prices as heightened relative demand outweighs the negative impact from losses due to physical risk events.

Combined: There are substantial declines in equity prices across indices and most sectors in the combined scenario. The Nikkei 225, FTSE 100 and S&P 500 all experience declines of up to 20% at one year. Equity prices in the UK, US and Japan exhibit a consistent pattern in response to both the physical and transition risk scenario, characterized by a decline in demand leading to reduced corporate earnings. The reaction of sectoral equity prices to the physical and transition scenario varies based on the carbon intensity and demand elasticity of each sector.

Sectors with a higher exposure to household expenditure, such as electricity and manufacturing, witness a less pronounced impact on demand. Consequently, these sectors experience an increase in equity prices, as the heightened demand outweighs the negative effects from losses due to physical hazard events. Conversely, mining and air transport are more severely affected by the imposition of the carbon tax, leading to a decline in demand and reduced corporate earnings, thereby causing equity prices to fall.

Credit

Asset Class	Region	Sector	Risk Factor	ISDA Proposed Shocks											
				Transition Risk				Physical Risk				Combined			
				1D	10D	3M	1Y	1D	10D	3M	1Y	1D	10D	3M	1Y
Credit (absolute spread change, in basis points)	Europe	Air Transport		20	20	70	110	25	50	75	125	20	110	125	150
		Electricity		20	30	80	120	25	50	100	125	25	100	125	150
		Mining & Quarrying		25	50	100	130	25	75	100	150	35	100	130	200
		Manufacture Chem/Chem Prods		25	30	80	120	25	75	100	150	30	110	130	150
		Land Transport		20	20	80	120	25	50	75	125	25	80	110	150
	UK/USD		USD 5Y CDS on UK	10	20	40	75	10	30	40	75	10	30	50	90

Table 3: Credit Spreads Shocks

The base ratings for the credit spreads are based on BBB corporate bonds, and all spread changes are relative. There is a widening in credit spreads across all sectors in all three scenarios, consistent with the transition and physical risk shocks increasing the probability of company defaults across the economy. The combined scenario sees the largest widening of spreads, consistent with this scenario having the biggest impacts on GDP due to both physical and transition risks occurring. The mining and quarrying sector suffers the largest widening in spreads given the significant impact of the carbon tax, but all carbon-intensive sectors see widening spreads. In the transition risk scenario, spreads also widen most in the mining and quarrying sector – consistent with this sector being particularly badly affected and undergoing the largest fall in equity prices. The physical risk scenario sees larger increases in spreads than the transition risk scenario, reflecting the greater impacts of the physical risk shock on output and the economy – as evidenced by the larger declines in GDP in this scenario.

Interest Rates

Asset Class	Region	Risk Factor	ISDA Proposed Shocks											
			Transition Risk				Physical Risk				Combined			
			1D	10D	3M	1Y	1D	10D	3M	1Y	1D	10D	3M	1Y
Rates (absolute spread change, in basis points)	Asia	INDIA GOV 1D	35	90	120	190	-80	-120	-170	-400	-15	-15	-20	-60
		INDIA GOV 6M	30	80	110	180	-70	-110	-160	-350	-10	-15	-20	-50
		INDIA GOV 1Y	25	70	100	170	-60	-100	-150	-300	-5	-10	-15	-40
	Europe	GER GOV 1D	30	50	80	90	-20	-35	-45	-75	-10	-20	-25	-50
		GER GOV 6M	20	40	70	80	-15	-30	-40	-75	-5	-15	-20	-40
		GER GOV 1Y	10	30	60	70	-10	-25	-35	-65	-5	-10	-15	-35
	UK	GBP GOV 1D	30	60	80	80	-30	-40	-70	-140	-15	-20	-40	-70
		GBP GOV 6M	20	50	70	70	-25	-35	-60	-120	-10	-15	-30	-60
		GBP GOV 1Y	10	40	50	60	-20	-30	-50	-100	-10	-15	-30	-50
	US	USD GOV 1D	30	70	80	160	-10	-30	-40	-100	-10	-15	-25	-25
		USD GOV 6M	25	60	70	150	-10	-25	-35	-90	-5	-10	-20	-25
		USD GOV 1Y	20	50	60	140	-10	-20	-30	-80	-5	-10	-15	-20
	Other	BRL GOV 1D	35	90	120	190	-100	-170	-220	-500	-10	-15	-20	-70
		BRL GOV 6M	30	80	110	180	-90	-160	-210	-475	-10	-15	-20	-50
		BRL GOV 1Y	25	70	100	170	-80	-150	-200	-450	-5	-10	-15	-40

Table 4: Yield Curve Shocks

Transition Risk: In the transition risk scenario, yield curves rise across countries and maturities for both government bond and swap curves. The rises are associated with rate increases by central banks in response to higher inflation fueled by the introduction of the carbon tax. As central banks raise rates, investors seek higher returns to match the new interest rate environment. The increases in yield curves are smaller at longer maturities, reflecting the temporary nature of the inflation shock. The increases in yield curves are larger for India and Brazil, consistent with greater historical interest rate volatility in these countries. The increase in swap curve rates is consistent with the rise in risk-free rates due to higher inflation.

Physical Risk: In the physical risk scenario, yield curves fall across countries and maturities for government bond curves and shorter maturity swap curves. The declining yields are primarily attributed to the reduction in interest rates driven by declines in GDP, as central banks try to stimulate demand. As in the transition scenario, the drop in yields is smaller at longer horizons because this shock is not viewed as having large, permanent effects on the level of interest rates. The decrease in swap curves is consistent with a reduction in risk-free rates. India and Brazil see particularly large declines in yield curves, consistent with the significant impact of the physical risk shock on GDP and policy rates.

Combined: The combined scenario sees relatively modest impacts on yield curves across countries as the impacts of the transition risk shocks pushing yields up are more than offset by the impacts of the physical risk shocks pushing them down.

Foreign Exchange (FX)

Asset Class	Region	Risk Factor	ISDA Proposed Shocks											
			Transition Risk				Physical Risk				Combined			
			1D	10D	3M	1Y	1D	10D	3M	1Y	1D	10D	3M	1Y
FX (percentage change)	Asia	USDINR	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%
		USDJPY	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Europe	USDEUR	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	UK	USDGBP	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	Other	USDBRL	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%	-5%	-10%	-15%	-20%

Table 5: FX Shocks

Transition Risk: The US dollar appreciates against the emerging market currencies, as these economies are largely exporters of commodities from high-emitting sectors, so are more adversely affected by the imposition of a carbon tax. The US dollar remained unchanged against the Japanese yen, euro and sterling as the relative shocks on developed countries are similar.

Physical Risk: The US dollar appreciates against the Brazilian real and Indian rupee as the interest rate shocks for the emerging markets are more severe compared to developed countries, given their economies are more vulnerable to large declines in GDP. The yields for these countries fall sharply in response to a decline in interest rates. The US dollar remains unchanged against the Japanese Yen, euro and sterling as the relative shocks on developed countries are similar.

Combined: As with the transition and physical risk scenarios, the US dollar appreciates against the Brazilian real and Indian rupee, as these economies are large exporters of goods from high-emitting sectors and are therefore more severely affected by the carbon tax, together with a large decline in GDP resulting from physical risk events.

Commodities and Mortgage-backed Securities (MBS)

Asset Class	Region	Risk Factor	ISDA Proposed Shocks											
			Transition Risk				Physical Risk				Combined			
			1D	10D	3M	1Y	1D	10D	3M	1Y	1D	10D	3M	1Y
Commodities (percentage change)	Other	GOLD	5%	10%	15%	20%	5%	10%	15%	20%	5%	15%	25%	30%
		CBOT CORN	-5%	-5%	-5%	-5%	-5%	-5%	-5%	-5%	-10%	-10%	-15%	-20%
		COAL PRICE	-10%	-20%	-30%	-40%	-10%	-15%	-25%	-30%	-10%	-25%	-30%	-35%
		WTI CRUDE	-5%	-10%	-20%	-30%	-10%	-25%	-20%	-30%	-10%	-20%	-25%	-35%
MBS	US	US RMBS	-5%	-10%	-15%	-20%	-5%	-15%	-20%	-25%	-10%	-15%	-25%	-40%

Table 6: Commodity and MBS Shocks

Transition Risk: Gold prices increase as investors perceive this as a 'flight to safety' sector in economic turmoil. Coal, corn and crude prices drop as GDP declines, causing demand to fall. There is a larger impact on oil and coal prices, as these are directly adversely affected by the increase in carbon tax. The shocks for soft commodities assume second-order effects from increased energy prices. Equally for the RMBS, the impact of increasing inflation, falling output and rising interest rates leads to increased expected mortgage losses and falls in the rise in prices of raw materials within this carbon-intensive sector will affect company profits, resulting in a reduction in the underlying mortgage value.

Physical Risk: Gold is expected to increase as it serves as a safe haven after severe negative equity indices shocks. Coal, corn and crude oil prices fall sharply given the overall impact of lower global demand, outweighing the impact of a reduction in supply. Lower demand leads to lower earnings, causing commodity prices to fall. The global economic slowdown will lead to a decline in demand for RMBS, as borrowers encounter financial difficulties and struggle to meet mortgage payments.

Combined: The perception of gold as a safe haven pushes prices higher following severe negative equity indices shocks. The negative equity indices shock directly influences the price of commodities as businesses cut production and consumers reduce spending. There is a larger impact on oil and coal prices, as these are directly adversely affected by the increase in carbon tax. Similarly, in the case of RMBS, the economic slowdown and declining GDP cause a reduction in demand for property and the underlying RMBS.

3.5.3. Impact Assessment

An impact assessment using a set of hypothetical instruments has been developed to complement the market risk factor shocks and to provide an illustrative indication of the potential impacts of climate risk on the trading book. The hypothetical instruments for this pilot exercise have been selected by leveraging previous EBA benchmarking exercises. These instruments have been 'shocked' using the scenarios that have been generated as part of this exercise.

The instruments cover the main advanced economy regions together with some emerging markets. The main asset classes are covered (equities, government bonds, swaps, FX and commodities), including sectoral equity and credit impacts for the EU.

The impact assessment is carried out for the instruments in the list using pricing models to calculate the relative change in the value, with results summarised in table below. The relative change in value measures the impact of the market risk shocks when applied to the physical, transition and combined scenarios. A detailed model formulation is presented in Appendix A, but an overview of the approach is described in this section. The impact assessment therefore provides benchmark heuristics for the representative market instruments.

The results of the impact assessment are presented in Table 7 below and results are consistent with the market risk shocks that have been applied as per the relevant physical, transition and combined market risks. The results reveal the nonlinear impact of the market factor shocks, as they combine a number of market shocks together that vary by instrument. All instruments used a 10-day liquidity horizon.

For example, the futures are influenced both by the relevant risk-free rate and the market risk shocks which have been applied to the underlying instruments price. Using the cost of carry method, we obtain the relative change in values under various scenarios. The short future increases in value when the value of the underlying asset decreases as we apply the market risk shock to the underlying's value. So, for example, the short Nikkei 225. Futures rise in value across all three consistent with the falls in equity prices in all three scenarios. Conversely, the long future's relative value falls when the value of the underlying asset decreases. For example, the long S&P futures falls in value across all three scenarios, consistent with the falls in equity prices in all three scenarios.

Asset Class	Region	Instruments	Physical Minus Base	Transition Minus Base	Combined Minus Base
Equities	Asia	Short Nikkei 225 Futures	9.2%	10.3%	9.8%
	Europe	Long S&P 500 Futures	9.9%	10.1%	10.0%
		Short EUR Equity Futures	1.9%	2.2%	2.0%
		Long Call Option. Underlying EUR Pharmaceutical Equity	-12.0%	-9.0%	-13.7%
		Long EUR Pharmaceutical Equity	-8.7%	-10.7%	-11.8%
	UK	Long Call Option, Underlying FTSE 100	-7.5%	-8.0%	-12.5%
Credit (absolute spread change, in bps)	Europe	Long EUR CDS on Insurance Equity	3.0%	-2.3%	1.3%
		Long EUR CDS on Energy Equity	2.9%	-2.3%	1.3%
		Long EUR CDS on Automobile Equity	3.0%	-2.3%	1.3%
		Long EUR CDS on iTraxx Europe Index On-the-run Series	2.7%	-2.1%	1.2%
	UK	Long USD CDS on the UK	1.6%	0.4%	2.0%
Rates (absolute rate change, in bps)	Europe	Long Germany Government Bond EUR1,000,000	1.3%	-1.3%	0.5%
		Two-year EUR Swaption on Five-year IRS EUR – Pay Fixed Rate and Receive Floating Rate	0.8%	-0.7%	0.3%
	UK	Two-year IRS GBP – Receive Fixed Rate and Pay Floating Rate	-3.7%	3.7%	8.6%
	Emerging Markets	Long Brazil Government Bond USD1,000,000	8.5%	-3.2%	0.3%
FX (percentage change)	Europe	Six-month USD/EUR Forward Contract	-0.1%	-0.2%	-0.1%
		Long Call Option EUR10,000,000	2.0%	-7.3%	-6.8%

Table 7: Impact Assessment Results

3.5.4. Sensitivity Analysis and Benchmarking Results

The macroeconomic result from this pilot exercise was benchmarked against other regulatory climate stress tests. This included the ECB's disorderly transition scenario, the Bank of England's (BOE) Annual Cyclical Scenario (ACS), the BOE's late action scenario under the Climate Biennial Exploratory Scenario and the Federal Reserve's Comprehensive Capital Analysis and Review (CCAR) severely adverse scenario.

Additionally, the 1-year transition risk market factor shocks were benchmarked against the 2022/3 BOE Annual Cyclical Stress test (ACS) transition risk scenario, The Federal Reserve Bank's comprehensive capital analysis and review (CCAR) severely adverse scenario and the European Central Bank (ECB) disorderly transition scenario. The table detailing the macroeconomic and market risk benchmarking results can be found in Table 8 to Table 11 in Appendix A.

4. Concluding Comments and Next Steps

In this paper, a conceptual framework developed by ISDA has been used to produce three climate risk scenarios for the trading book. The scenarios include a detailed set of market risk factors. A key consideration for this exercise is the transmission from climate-adjusted macroeconomic variables to market risk factors. While conventional regulatory climate scenario analysis exercises predominantly concentrate on assessing the impact of climate on macroeconomic variables, the primary objective of this pilot exercise was to develop a methodology for modelling the impact on market risk factors. The scenarios produced are intended to support banks as they work to conduct climate risk scenario analysis for their trading books. The exercise has also served as a pilot of the conceptual framework.

Overall, the conceptual framework proved an invaluable guide for trading book climate scenario analysis in the trading book described in this paper. This exercise proved that all of the stages and key considerations outlined in the conceptual framework are necessary to successfully conduct climate scenario analysis for the trading book and assess the impact of climate-related risk on market risk factors. More specifically, this pilot exercise highlighted stages of the conceptual framework that are especially important for future climate scenario analysis for the trading book: scope of country and sectoral coverage and modelling choices.

As this was a pilot exercise, a number of choices was made to limit scope. Only six regions were chosen to represent the largest global economies. Other than the EU, the other regions were modelled at a country level, incorporating the aggregated effects of the sectors within that specific location. It would be desirable to include more countries in future exercises – particularly those highly sensitive to commodity markets. The ISDA working group expressed interest in including Australia, Canada, China and South Africa in future work to better capture the impact of commodity markets on these countries and to provide a wider coverage for Foreign Exchange shocks.

In terms of sectors, market risk shocks at a sectoral level were modelled for one region (the EU). Five high-emitting sectors were selected with input from the working group, along with one low-carbon sector (publishing activities) as a control. Richer sectoral granularity would provide analysis on how market participants switch to green alternative sectors (eg, the differentiation between 'green' and 'brown' sectors), which would provide a more in-depth explanation of the resulting market risk shocks.

However, including more regions and sectors would increase the complexity and size of the modelling challenge. The need to balance the complexity of the modelling approach used for shock generation with the scope of the exercise was an issue highlighted in the conceptual framework and reinforced by this exercise.

From a modelling perspective, it is crucial to recognize that climate risk factors drive the behavior of macroeconomic variables, ultimately influencing market risk factors. There are several ways to model climate-adjusted macroeconomic variables, and the choice of model will yield different market risk factor results. For this exercise, an ABM was used, which allowed the exploration of sectoral impacts and dynamics in a detailed way. As highlighted in the conceptual framework, it is important for all scenario analysis to carefully consider the appropriate modelling framework based on the use case and the portfolios of interest.

The crowdsourcing aspect of the scenario analysis was an integral part of this pilot exercise to manage the risks of model uncertainty. Drawing on subject matter expertise of the working group meant a broad set of views on the anticipated shock movements and sizes were captured to overlay on the modelling outputs. This allowed the climate risk scenarios to be calibrated to provide plausible market risk factor shocks that aligned with the ISDA working group's expectations on market risk movements.

The impact assessment offers benchmark heuristics for representative market instruments and provides insights into the valuation of such instruments under climate scenarios. A holistic P&L assessment would require consideration of additional components, including hedging positions, basis risk and funding.

Furthermore, a capital assessment would require consideration of the impact to Risk-Weighted Assets (RWAs). These issues were not within the scope of this exercise but might be included in future work.

Short-term climate scenario analysis is still an evolving area and firms are continuing to develop their capabilities to measure climate risk in the trading book. The climate scenario analysis landscape is expanding to include climate-related risks in the trading book and the purpose of this pilot exercise was to provide firms with climate scenarios to consider and use as an input to their internal scenario analysis. Some firms indicated that these scenarios would be used to inform their internal risk management processes and serve as input into their internal capital adequacy assessment process (ICAAP).

The methodology outlined in this report serves as a first step in developing a standard for measuring climate-related risks in the trading book. A potential next step for the ISDA working group is to continue the expansion of scenarios to include additional regions and sectors, which will support firms in accelerating their climate scenario analysis capabilities in line with regulatory expectations.

5. Appendix A

Macro-economic Benchmarking Results

			ISDA Transition Risk (Q2 2023)	ISDA Physical Risk (Q2 2023)	ISDA Combined Scenario (Q2 2023)	ECB 2022 Disorderly Transition Baseline (Q1 2022)	ECB 2022 Disorderly Transition ST min base (Q1 2022)	BOE ACS ST 2022/3 (Q2 2022)	CBES 2021 Late Action (LA)	CCAR 2023 Severely Adverse (Q1 2023)
VARIABLE	**UNIT**	**GEOGRAPHY**	**y1**	**y1**	**y1**	**Y1**	**y1**	**y1**	**y1**	**y1**
	MACRO VARIABLES									
Gross Domestic Product (GDP)	Delta of shock vs baseline	UNITED KINGDOM	-1.40%	-4.30%	-4.90%	1.63%	-2.36%	-3.87%	-0.69%	-2.50%
		EU (FRANCE)	-0.70%	-2.70%	-2.90%	2.21%	-2.19%	-4.30%	-1.24%	-5.00%
		UNITED STATES	-0.60%	-1.60%	-2.00%	3.00%	-4.41%	-5.60%	-1.05%	-2.70%
		JAPAN	-2.60%	-5.60%	-6.70%	1.32%	-4.19%		-2.47%	-6.60%
		REST OF THE WORLD				3.39%	-3.67%	-4.70%	-0.78%	
Inflation rate	Delta of shock vs baseline	UNITED KINGDOM	2.70%	-2.60%	1.20%	2.23%	1.74%	5.60%	3.68%	-0.80%
		EU (FRANCE)	1.20%	-0.50%	1.30%	-0.18%	0.07%	8.13%	4.00%	-1.40%
		UNITED STATES	1.40%	-0.80%	1.30%	2.87%	2.12%			1.00%
		JAPAN	1.90%	-3.70%	-1.10%	0.57%	1.08%			-2.00%
		REST OF THE WORLD				2.31%	1.88%			
Short term interest rate	Delta of % rate p.a.	UNITED KINGDOM	0.60%	-1.70%	1.40%	0.10%	0.74%	2.99%	-0.79%	
		EU (FRANCE)	0.60%	-0.70%	-0.70%	-0.18%	-0.41%	3.59%	-0.41%	
		UNITED STATES	0.90%	-1.00%	-0.20%	0.25%	0.32%	3.22%	-0.72%	-4.10%
		JAPAN	0.50%	-2.00%	-1.30%	-0.07%	-0.56%			
		REST OF THE WORLD				0.038	-0.37%			

Table 8: Benchmarked Macro-economic Values[14]

The base line year for each scenario is specified in brackets in the respective headings of the table. The benchmarking results indicate that there is considerable variation across all the different exercises, making benchmarking somewhat difficult. This is not entirely surprising given they are focused on different risks. For the ISDA transition risk scenario, the GDP shock is broadly in line with the CBES late action scenario and a little smaller than the ECB disorderly transition scenario. And the transition impacts are smaller than the BoE ACS and CCAR scenarios. On the other hand, the physical risk and combined scenarios see larger GDP impacts than the CBES scenario, with the GDP shocks for the UK and Japan similar to the ACS and CCAR. Regarding inflation under the transition risk shock, this exhibits greater severity compared to the ECB Disorderly shock across all regions, although there is a closer alignment when comparing the short-term interest rate. It is noteworthy that both inflation and the short-term interest rate for the EU are negative, whereas the ISDA shock is positive.

[14] SSP245 baseline data can be found here: https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=40

Market Risk Factors Sensitivity Analysis and Benchmarking Results

The tables below detail the results of the sensitivity analysis conduct for the physical risk scenario. Two additional temperature sensitivities were produced to assess the impact of the physical risk shocks at 1 and 0.5 degrees Celsius temperatures. These results suggest smaller impacts on the market risk factors at the lower temperatures and have been presented alongside other regulatory stress test results for comparison purposes.

Equities

REGION	SECTOR	RISK FACTOR	ISDA Physical Risk 1.5C				ISDA Physical Risk 1C				ISDA Physical Risk 0.5C				BOE ACS 2023 TR Shocks				CCAR 2023 TR Shocks	ECB 1y market risk shocks
			1 D	10 D	3 m	1 y	1 D	10 D	3 m	1 y	1 d	10 D	3 m	1 y	1 d	10D	1 m	1 y	Spot	1 y
Asia		NIKKEI225	-5%	-10%	-20%	-25%	-4%	-10%	-17%	-19%	-2%	-3%	-6%	-10%	-7%	-21%	-30%	-51%	-32%	
		EUROSTOXX50		-				-				-			-7%	-22%	-33%	-49%	-35%	
Europe	Air Transport		-5%	-10%	-15%	-20%	0%	0%	1%	2%	-0%	-0%	1%	1%	-					-7%
	Electricity		5%	5%	10%	15%	4%	3%	9%	20%	1%	1%	4%	6%						-11%
	Mining & Quarrying		0%	0%	0%	0%	-1%	0%	0%	1%	-0%	-0%	0%	0%						-17%
	Publishing Activities		0%	0%	0%	5%	0%	0%	3%	9%	-0%	-0%	1%	4%						-
	Manufacture of Chem/Chem Prods		5%	10%	15%	20%	7%	5%	14%	17%	1%	2%	4%	6%						-6%
	Land Transport		-5%	-10%	-15%	-20%	0%	-1%	0%	1%	-0%	-0%	-0%	0%						-10%
US		S&P 500	-5%	-10%	-15%	-20%	-4%	-5%	-9%	-16%	-1%	-2%	-3%	-3%	-8%	-20%	-28%	-47%	-26%	
UK		FTSE100	-5%	-10%	-15%	-20%	-3%	-6%	-8%	-12%	-1%	-2%	-3%	-5%	-6%	-21%	-29%	-45%	-30%	

Table 9: Equity Market Risk Factor Benchmarking Results

Interest Rates

REGION	RISK FACTOR	ISDA Physical Risk 1.5C				ISDA Physical Risk 1C				ISDA Physical Risk 0.5C				BOE ACS 2023 TR Shocks				CCAR 2023 TR Shocks	ECB 1y market risk shocks
		1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	Spot	1 Y
Other	INDIA GOV 1Y	-60	-100	-150	-300	-44	-61	-71	-213	-12	-24	-38	-65	60	115	150	370	-71	
	INDIA GOV 5Y	-50	-90	-120	-280	-37	-57	-69	-199	-10	-22	-34	-58	45	85	115	290	-61	
Europe	GER GOV 1Y	-10	-25	-35	-65	-5	-11	-16	-25	-2	-6	-6	-7	65	130	175	440	-93	
	GER GOV 5Y	-5	-20	-30	-55	-5	-9	-14	-19	-1	-5	-6	-6	50	100	130	320	-71	
	EUR SW 1Y	0	-15	-25	-60	-1	-8	-14	-24	2	-1	-4	-6	70	140	185	460	-78	
	EUR SW 5Y	0	-5	-15	-45	0	-2	-11	-17	4	3	-2	-4	50	100	130	330	-61	
UK	GBP GOV 1Y	-20	-30	-50	-100	-12	-19	-34	-88	-4	-9	-12	-35	65	125	165	410	-90	28
	GBP GOV 5Y	-15	-25	-45	-90	-10	-17	-27	-75	-4	-4	-11	-24	55	110	145	360	-69	
	GBP SW 1Y	-10	-15	-35	-100	-8	-13	-31	-86	0	-4	-10	-33	65	130	170	420	-90	
	GBP SW 5Y	0	-5	-30	-90	-4	-7	-24	-72	0	3	-6	-20	50	100	130	320	-69	
US	USD GOV 1Y	-10	-20	-30	-80	-4	-13	-17	-28	-2	-5	-7	-10	60	115	150	370	-153	74
	USD GOV 5Y	-5	-15	-25	-70	-3	-8	-14	-23	-1	-3	-5	-7	45	85	115	290	-106	
	USD SW 1Y	-10	-15	-30	-80	-2	-10	-15	-27	1	-2	-5	-9	50	100	135	340	-153	
	USD SW 5Y	0	-5	-20	-70	0	0	-11	-21	3	2	-3	-5	45	85	110	270	-106	
Other	BRL GOV 1Y	-80	-150	-200	-450	-52	-82	-121	-309	-22	-35	-41	-128	105	200	265	650	332	
	BRL GOV 5Y	-70	-140	-190	-425	-43	-76	-114	-261	-22	-33	-38	-111	-	-	-	-	464	

Table 10: Interest Rate Market Risk Factor Benchmarking Results

FX and Commodities

ASSET CLASS	REGION	RISK FACTOR	ISDA Physical Risk 1.5C				ISDA Physical Risk 1C				ISDA Physical Risk 0.5C				BOE ACS 2023 TR Shocks				CCAR 2023 TR Shocks	ECB 1y market risk shocks
			1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	1 D	10D	3 M	1 Y	Spot	1 Y
FX (percentage change)	Asia	USDINR	-5%	-10%	-15%	-20%	0.6%	0.7%	0.9%	2.0%	0.1%	0.2%	0.5%	0.7%	5%	10%	13%	20%	-2%	
		USDJPY	0%	0%	0%	0%	0.2%	0.2%	0.4%	0.6%	0.1%	0.1%	0.2%	0.3%	3%	5%	7%	10%	10%	
	Europe	USDEUR	0%	0%	0%	0%	0.0%	-0.1%	0.0%	0.1%	0.0%	0.0%	0.1%	0.1%	0%	0%	0%	0%	6%	0.9%
	UK	USDGBP	0%	0%	0%	0%	-0.1%	-0.1%	-0.2%	-0.5%	0.0%	0.0%	-0.1%	-0.1%	0%	0%	0%	0%	5%	0.9%
	Other	USDBRL	-5%	-10%	-15%	-20%	0.6%	1.0%	1.0%	3.2%	0.2%	0.3%	0.4%	1.0%	10%	20%	27%	40%	-13%	
Commodities (percentage change)	Other	GOLD	5%	10%	15%	20%	3%	10%	8%	13%	1%	2%	3%	5%	5%	15%	20%	50%	15%	
		CBOT CORN	-5%	-5%	-5%	-5%	-5%	-7%	-6%	-7%	-2%	-1%	-2%	-3%					-12%	
		COAL PRICE	-10%	-15%	-25%	-30%	-7%	-8%	-19%	-16%	-2%	-3%	-6%	-6%					-50%	
		WTI CRUDE	-10%	-25%	-20%	-30%	-6%	-10%	-11%	-15%	-2%	-4%	-3%	-4%	10%	30%	50%	40%	-34%	

Table 11: FX and Commodities Market Risk Factor Benchmarking Results

Results

See "Climate Scenario Results.xlsx".

6 Appendix B: Detailed Modelling Methodology

This below sections outline the detailed methodology for the mapping of climate shocks to market risk factors. The full details of all models used in the exercise are described, from the climate model, through the macroeconomic agent-based model to the variety of expansion models used to generate the market risk shocks. All models are described with reference to the appropriate academic literature, which encompasses traditional models from quantitative finance and modern machine learning-based approaches.

The below sections are not intended as an academic article and makes no claims on originality. Instead, it synthesises, builds upon and implements the methodologies and open-source numerical libraries developed by existing researchers. This document is therefore intended as a description of how our Python-based forecasting models for all three domains (developed by the Traded and Quantitative Risk group in the Deloitte London office) are consistently coupled using three mathematical frameworks. Consequently, the text below draws directly from and adopts approaches as indicated in the cited research.

6.1 Modelling Climate

Earth System Models (ESMs) are integral to our detailed understanding of how the climate system responds and hence what future states of the world might look like in response to changing greenhouse gas (GHG) and aerosol emissions. The lack of empirical precedent for human-induced climate change makes modelling - for scenario generation - a necessity. However, ESMs are so computationally expensive that only a limited set of experiments are possible during a cycle of the Coupled Model Intercomparison Project (CMIP). This constraint on the quantity of experiments necessitates the use of simpler, less granular climate models (SCMs) to provide probabilistic assessments and hence enable the exploration of additional experiments and scenarios.

6.1.1 Simple Climate Models are Powerful

In general, SCMs are able to simulate the globally averaged emission → concentration → radiative forcing → temperature response pathway and can be tuned to emulate an individual ESM (or multi-model mean). In general, SCMs are considerably less complex than three dimensional, gridded ESMs, which explicitly model dynamical and physical processes (therefore outputting many hundreds of variables, whereas SCMs instead are globally averaged or cover large regions). SCMs parameterize many processes, resulting in many fewer output variables. This reduction in complexity means that SCMs are much quicker than ESMs in terms of runtime. The result is that most SCMs can run tens of thousands of years of simulation per minute on an "average" personal computer, whereas ESMs may take several hours to run a single year on hundreds of supercomputer processors. Most SCMs are also much smaller in terms of lines of code, being be on the order of thousands of lines, compared to ESMs which can be up to a million lines (Alexander and Easterbrook, 2015).

6.1.2 Climate Modelling Needs to be Dynamic

An important innovation of the IPCC 5th Assessment Report (Myhre et al., 2013) was the introduction of a transparent set of equations (the AR5-IR model) for use in the calculation of GHG metrics. However, that model did not adequately reproduce the evolution of the integrated impulse response to emissions over time, due to the lack of non-linearity in the model of the carbon cycle. The Finite Amplitude Impulse Response (FAIR) model v1.0 (Millar et al., 2017) introduced a state dependence to the AR5-IR carbon cycle. In Version 2.0, Leach et al. (2021) maintain the ability to simulate the atmospheric response to a wide range of GHGs and aerosol emissions, while attempting to significantly reduce the complexity of model structure. We follow the model provided in FaIR Version 2.0.0, where Leach et al (2021) propose a set of six equations that are demonstrated to be sufficient to capture the global mean climate system response to GHG and aerosol emissions. Whilst the trading book scenarios considered here are short-term, it is preferable to design a generalized methodology which could be extended to the banking book. Therefore, dynamics with a longer timescale than trading book scenarios (like emission dynamics) are relevant for discussion here.

6.1.3 Six Equations Capture Climate Behavior

The six equations shown in Figure 7 are simple but flexible and tuneable enough to emulate the behaviour of several key processes within more complex models from CMIP6. The FAIR model is exceptionally quick to run on a desktop computer, making it ideal for ensemble analysis. Leach et al (2021) apply a constraint based on the current estimates of the global warming trend to a million-member ensemble, using the constrained ensemble to enable scenario-dependent projections and hence infer ranges for key properties of the climate system. Through these analyses, they show that simple climate models (unlike more complex models) are not themselves intrinsically biased “hot” or “cold”. Instead, it is the choice of parameters and how those are selected that determines the model response. The FaIR 2.0.0 model is able to reproduce the global climate system response to GHG and aerosol emissions with sufficient accuracy to be useful in a wide range of applications and therefore usable as a lowest-common-denominator model to provide consistency in different contexts.

6.1.4 Capturing Individual Cycles

As shown in Figure 7, terms without (t) are constants. The coloring divides the model into gas cycle, radiative forcing, and climate response components. The dashed grey line indicates the components identical to AR5-IR. Table 1 in Leach et al (2017) provides brief descriptions of each named parameter in the figure. We note that under the default parameterization, for all gases except carbon dioxide, the index i and associated sums can be removed as these gases are modelled as having a single atmospheric decay timescale only. Equations are described in full in Sect. 2.1 of Leach et al (2021).

6.1.5 The Short-term Impact on Temperature of a Doubling of CO_2

Borrowing directly from Millar et al 2017, projections of the response to anthropogenic emission scenarios, evaluation of some greenhouse gas metrics, and estimates of the social cost

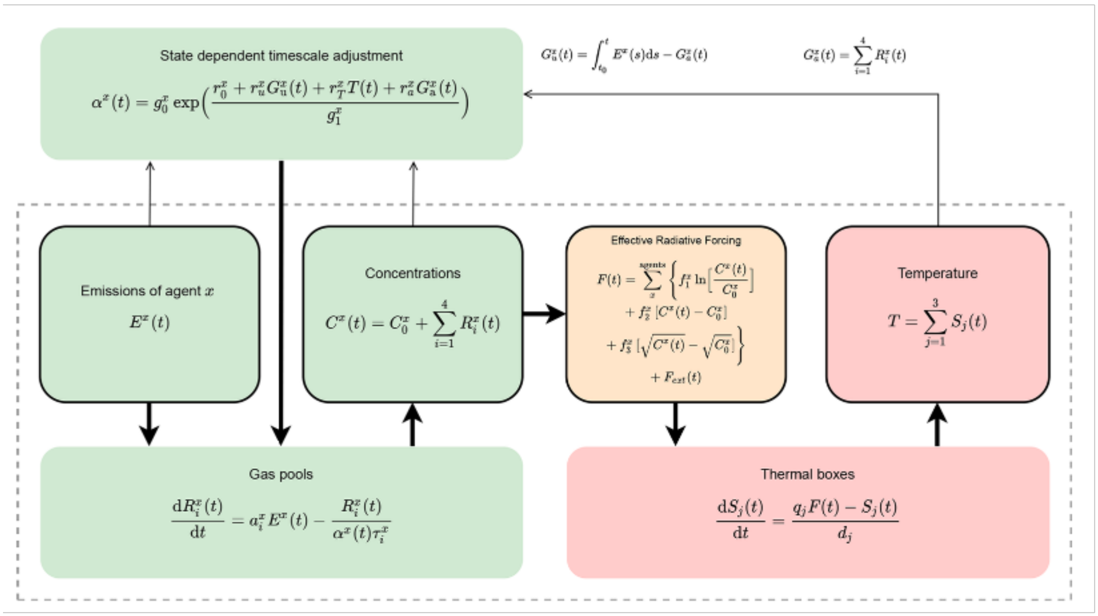


Figure 7: Schematic showing the Full FAIR Model Structure and Equations

Parameter	Units	Value	Analogue
F_{2x}	Wm^{-2}	3.74	The forcing due to CO_2 doubling
q_1	$KW^{-1}m^2$	0.33	Thermal equilibration of deep ocean
d_1	year	239.0	Thermal equilibration of deep ocean
q_2	$KW^{-1}m^2$	0.41	Thermal adjustment of upper ocean
d_2	year	4.1	Thermal adjustment of upper ocean

Figure 8: Parameter Names and Values for Temperature Impact

of carbon often require a simple model that links emissions of carbon dioxide ()CO_2) to atmospheric concentrations and global temperature changes. A key requirement of such a model is to reproduce typical global surface temperature and atmospheric CO_2 responses displayed by more complex Earth system models (ESMs) under a range of emission scenarios, as well as an ability to sample the range of ESM response in a transparent, accessible and reproducible form. Here we adapt the simple model of the Intergovernmental Panel on Climate Change 5th Assessment Report (IPCC AR5) to explicitly represent the state dependence of the CO_2 airborne fraction. In the particular case of the impact on temperature of an instantaneous doubling of CO_2, the transient climate response (TCR) of temperature to such a doubling can be estimated from the following equation:

$$\text{TCR} = F_{2x}\left(q_1\left(1 - \frac{d_1}{70}\left(1 - exp\left(\frac{-70}{d_1}\right)\right)\right) + q_2\left(1 - \frac{d_2}{70}\left(1 - exp\left(\frac{-70}{d_2}\right)\right)\right)\right) \quad (1)$$

where the variables have the values shown in Figure 8.

6.1.6 Coupling Climate and Economic Models

Due to the complexities in both climate and macro-economic models, the overall philosophy for coupling such complex models is to follow the FAIR approach and use non-linear impulse-response functions. In macroeconomic modelling it is generally agreed that consumers' re-

Economic Sectors	Physical Risk								
	Output per Worker in mln LCU α_s	Productivity of Intermediate Consumption β_s	Productivity of Capital κ_s	Depreciation Rate of Capital δ_s	Net Tax Rate on Production τ_s^k	Net Tax Rate on Products τ_s^Y	Household Investment Coefficient of the gth Product b_g^{CFH}	Capital Formation Coefficient of the gth Product b_g^{CF}	Household Consumption Coefficient of the gth Product b_g^{HH}
Agriculture [A]	0.0073	1.56	0.0455	0.00335	-0.0575	0.0481	0.0033	0.0039	0.019
Production [B-E]	0.0158	1.49	0.0836	0.00341	0.0065	0.0741	0.3726	0.2153	0.373
Construction [F]	0.0113	1.51	0.3074	0.00366	0.0050	0.0847	0.2989	0.5071	0.001
Distribution, transport, hotels and restaurants [G-I]	0.0076	2.02	0.1048	0.00372	0.0238	0.0533	0.0589	0.0000	0.150
Information and communication [J]	0.0130	2.11	0.1218	0.00745	-0.0029	0.0436	0.0969	0.1243	0.039
Financial and insurance [K]	0.0187	1.93	0.2241	0.00623	0.0103	0.0322	0.0000	0.0000	0.055
Real estate [L]	0.0737	4.44	0.1443	0.00187	-0.0028	0.0042	0.0046	0.0227	0.225
Professional and support activities [M-N]	0.0096	2.12	0.2487	0.00745	0.0060	0.0280	0.1625	0.1228	0.033
Government, health & education [O-Q]	0.0046	2.59	0.0845	0.00399	0.0019	0.0069	0.0000	0.0030	0.043
Other services [R-T]	0.0042	2.69	0.1031	0.00445	0.0101	0.0944	0.0023	0.0009	0.062

Figure 9: Climate-adjusted and Statistically Balanced Input-Output Matrix - UK

sponses to income and wealth shocks result in variations in consumption. During the last two decades, the world economy experienced major cyclicalities through a series of bubble–post-bubble environments. The major events included (but are not limited to) the dot-com bubble of 2000–2003, the global financial crisis of 2007–2010 and most recently the Covid-19 period. Evidence from these events suggests that households do not change their consumption habits immediately in response to such episodes. However, several macroeconomic and psychological factors appear to affect consumption in such volatile economic conditions. It is therefore not surprising that cyclical and non-linear (i.e. asymmetric and/or time varying) behavior in consumption and its components have been observed.

6.1.7 Sectoral Impact of Temperature Changes

Burke et al (2015) show that overall economic productivity is non-linear in temperature for all countries, with productivity peaking at an annual average temperature of 13^oC and declining strongly at higher temperatures, but with substantial variations between developed and developing countries. Hsiang et al. (2017) produce probabilistic impact projections of daily temperature and precipitation using the Surrogate/Model Mixed Ensemble (SMME) method, which employs probabilistic projections of global mean surface temperature (GMST) change produced using a simple climate model (SCM) very similar to the FAIR model described above, to weight the gridded temperature/precipitation projections from a multi-model ensemble of downscaled GCM output, and employs linear pattern scaling to produce 'model surrogates' that cover portions of the SCM-derived GMST probability distribution not present in the GCM ensemble.

6.1.8 Balancing the Input-Output Matrix

The final step of the climate modelling process is mapping temperature effects to individual economic sectors. This involves calibrating the impact of temperature changes by sector to ensure that the input-output matrix is correctly balanced and thereby avoid misleading sectoral macroeconomic results. From a mathematical perspective this involves rescaling a given square non-negative matrix $A \in Rn$×n to a doubly ≥ 0 stochastic matrix, where every row and column sums to one, by multiplying two diagonal matrices R and S. This is a fundamental process for analyzing and comparing matrices in a wide range of applications, including input-output analysis in economics, called the RAS approach (see Sugiyama et al 2018) . The final result of applying the temperature adjustments by sector and balancing the input-output table is indicated in Figure 9.

6.2 Macroeconomic ABM

The macroeconomic Agent-Based Model (ABM) is comprised of groups of hetrogeneous agents which interact and trade according to predefined rules and expectations. By observing and aggregating their behavior, the overall performance of the economy can be observed. The different types of agents are described qualitatively here, with their governing equations in the following subsection.
Agent-based models allow the bottom-up interactions of heterogeneous agents to govern the overall behavior of the system. For applications with no historical precedent, like climate change, it is essential to use methodologies that allow the capture of non-linear and unintuitive dynamics in complex systems. It is also possible to relax assumptions of general equilibrium models, like rational expectations, which limit their generalizability to real-world scenarios. An ABM that is similar to the one employed here has been successfully used to model various economic crises in the Euro area (Hommes & Poledna, 2023). The authors show that the model is used to predict a crisis that arises endogenously during the Great Recession without applying exogenous shocks. It was also used to predict the inflationary dynamics of the COVID-19 economic recovery. In previous and the present work, it is also able to do so with a level of granularity and transparency that is challenging to achieve from top-down modelling methodologies. For example, the interrogation of individual firm balance sheets to derive sectoral equity valuations in Section .

Firms:

The firm sector is composed of distinct industry sectors, the number of which varies with the region being modelled. The firm population of each sector is derived from business demography data, while firm sizes follow a power law distribution. Each firm is part of a certain industry and produces industry-specific output by means of labor, capital, and intermediate inputs from other sectors—employing a fixed coefficient (Leontief) production technology with constant coefficients. These productivity and technology coefficients are calculated directly from input-output tables. Firms are subject to fundamental uncertainty regarding their future sales, market prices, the availability of inputs for production, input costs, and cash flow and financing conditions. Based on partial information about their current status quo and its past development, firms need to form expectations to estimate future demand for their products, their future input costs, and their future profit margin. According to these expectations, which are not necessarily realized in the future, firms set prices and quantities. Firms form these expectations using simple autoregressive time series models (e.g., AR (1) expectations). These expectations are parameter-free, as agents learn the optimal AR (1) forecast rule that is consistent with two observable statistics, the sample mean and the sample autocorrelation. Output is sold to households as consumption goods or investment in dwellings and to other firms as intermediate inputs or investment in capital goods, or it is exported. Firm investment is conducted according to the expected wear and tear on capital. Firms are owned by investors (one investor per firm), who receive part of the profits of the firm as dividend income.

Households:

The household sector consists of employed, unemployed, investor, and inactive households, with their respective numbers obtained from census data. Employed households supply labor and earn sector-specific wages. Unemployed households are involuntarily idle, and receive unemployment benefits, which are a fraction of previous wages. Investor households obtain dividend income from firm ownership. Inactive households do not participate in the labor market and receive social benefits provided by the government.

Additional social transfers are distributed equally to all households (e.g., childcare payments). All households purchase consumption goods and invest in dwellings which they buy from the firm sector. Due to fundamental uncertainty, households also form AR (1) expectations about the future that are not necessarily realized. Specifically, they estimate inflation using an optimal AR (1) model to calculate their expected net disposable income available for consumption.

Government:

The main activities of the government sector are consumption on retail markets and the redistribution of income to provide social services and benefits to its citizens. The amount and trend of both government consumption and redistribution are obtained from government statistics. The government collects taxes, distributes social as well as other transfers, and engages in government consumption. Government revenues consist of (1) taxes: on wages (income tax), capital income (income and capital taxes), firm profit income (corporate taxes), household consumption (value added tax), other products (sector-specific, paid by industry sectors), firm production (sector-specific), as well as on exports and capital formation; (2) social security contributions by employees and employers; and (3) other net transfers such as property income, investment grants, operating surplus, and proceeds from government sales and services.

Government expenditures are composed of (1) final government consumption; (2) interest payments on government debt; (3) social benefits other than social benefits in kind; (4) subsidies; and (5) other current expenditures. A government deficit adds to its stock of debt, thus increasing interest payments in the periods thereafter.

Commercial Bank:

The banking sector obtains deposits from households as well as from firms and provides loans to firms. Credit creation is limited by minimum capital requirements, and loan extension is conditional on a maximum leverage of the firm, reflecting the bank's risk assessment of a potential default by its borrower. Bank profits are calculated as the difference between interest payments received on firm loans and deposit interest paid to holders of bank deposits, as well as write-offs due to credit defaults (bad debt).

Central Bank:

The central bank sets the policy rate based on implicit inflation and growth targets, provides liquidity to the banking system (advances to the bank), and takes deposits from the bank in the form of reserves deposited at the central bank. Furthermore, the central bank purchases external assets (government bonds) and thus acts as a creditor to the government. Interest rates are set, according to the Taylor rule.

6.2.1 Macroeconomic ABM Equations

This section describes the equations that govern the behavior of the different agents in the macroeconomic Agent Based Model (ABM). Each agent acts independently within bounded rationality: they form expectations based on partial information. Expectations are generally formed through autoregressive processes of lag order one i.e. based on their current and previous state.

Firms

Sales:

$$Q_i(t) = \text{min}(S_i(t-1) + Y_i(t), Q_i^d(t)), \tag{2}$$

where $S_i(t-1)$ is the inventory of finished goods, $Q_i^d(t)$ the demand, and $Y_i(t)$ the production of goods by firm i.

Price setting and supply:

$$\begin{aligned} P_i(t) = &\overbrace{\left(\frac{\bar{w}_i(1+\tau^{\text{SIF}})\bar{P}^{\text{HH}}(t-1)(1+\pi^{\text{e}}(t))}{\bar{\alpha}_i}\right)}^{\text{Unit labor costs}} \\ &+ \overbrace{\left(\frac{1}{\beta_i}\sum_g a_{sg}\bar{P}_g(t-1)(1+\pi^{\text{e}}(t))\right)}^{\text{Unit Material costs}} \\ &+ \overbrace{\left(\frac{\delta_i}{\kappa_i}\bar{P}^{\text{CF}}(t-1)(1+\pi^{\text{e}}(t))\right)}^{\text{Unit capital costs}} \\ &+ \overbrace{\left(\tau_i^{\text{Y}}\bar{P}_i(t-1)(1+\pi^{\text{e}}(t))\right)}^{\text{Unit net taxes/subsidies products}} \\ &+ \overbrace{\left(\tau_i^{\text{K}}\bar{P}_i(t-1)(1+\pi^{\text{e}}(t))\right)}^{\text{Unit net taxes/subsidies production}} \\ &+ \overbrace{\left(\bar{\pi}_i\bar{P}_i(t-1)(1+\pi^{\text{e}}(t))\right)}^{\text{Target unit operating surplus}} \quad \forall i \in I_s, \end{aligned} \tag{3}$$

where $\bar{\alpha}_i$ indicates the average productivity of labor, $\bar{w}_i$ are gross wages indexed by the consumer price index $\bar{P}^{\text{HH}}(t)$, and including employers' contribution to social insurance charged at a rate τ^{SIF}; $\frac{1}{\beta_i}\sum_g a_{sg}$ are unit real expenditures on intermediate input by industry s on good g weighted by the average product price index $\bar{P}_g(t)$ for good g; $\frac{\delta_i}{\kappa_i}$ are unit real capital costs due to depreciation δ_i is the firm's capital depreciation rate and κ_i is the productivity coefficient for capital); $\bar{P}^{\text{CF}}(t)$ is the average price of capital goods, τ_i^{Y} and τ_i^{K} are net tax rates on products and production, respectively, and $\bar{\pi}_i = 1 - (1 + \tau^{\text{SIF}})\frac{\bar{w}_i}{\bar{\alpha}_i} + \frac{\delta_i}{\kappa_i} + \frac{1}{\beta_i} - \tau_i^{\text{K}} - \tau_i^{\text{Y}}$ is the operating margin. Here, $\pi^{\text{e}}(t)$ is the expected inflation rate.

Production:

$$Y_i(t) = \min(Q_i^{\text{s}}(t), \beta_i M_i(t-1), \alpha_i(t) N_i(t), \kappa_i K_i(t-1)), \tag{4}$$

where $Q_i^{\text{s}}(t)$ is desired production of firm i, $\alpha_i(t)$ is the productivity of labor of firm $i \in I_s$, and β_i and κ_i are productivity coefficients for intermediate inputs and capital, respectively.

Investment:

$$I_i(t) = \begin{cases} \sum_g I_{ig}^{\text{d}}(t) & \text{if the firm successfully realized the investment plan,} \\ < \sum_g I_{ig}^{\text{d}}(t) > & \text{if all firms visited could not satisfy its demand,} \end{cases} \tag{5}$$

The amount of realized investment therefore depends on the search-and-matching process on the capital goods market.

Intermediate Inputs:

$$M_i(t) = \begin{cases} \sum_g \Delta M_{ig}^{d}(t) & \text{if the firm successfully realized its plan,} \\ < \sum_g \Delta M_{ig}^{d}(t) > & \text{if all firms visited could not satisfy its demand,} \end{cases} \tag{6}$$

In the intermediate goods market, too, the amount of realized purchases of intermediate goods depends on a search-and-matching process.

Employment:

$$N_i(t) = \begin{cases} N_i^{\text{d}}(t) & \text{if the firm successfully fills all vacancies,} \\ < N_i^{\text{d}}(t) > & \text{if there are unfilled vacancies.} \end{cases} \tag{7}$$

Here, whether vacancies are filled or not depends on the search-and-matching mechanism in the labor market.

External finance:

$$\Delta L_i^{\text{d}}(t) = \max(0, \Delta D_i^{e}(t) - D_i(t-1)), \tag{8}$$

where $\Delta L_i^{\text{d}}(t)$ is a bank loan (i.e., new credit) to cover a firm's financing gap if the internal financial resources of the firm are not adequate to finance its expenditures.

Accounting:

$$E_i(t) = D_i(t) + \sum_g a_{sg} \bar{P}_g(t) M_i(t) + P_i(t) S_i(t) + \bar{P}^{\text{CF}}(t) K_i(t) - L_i(t) \quad \forall i \in I_s, \tag{9}$$

where $D_i(t)$ is the deposit, $\bar{P}_g(t)$ the price index for the principal good g, $S_i(t)$ the inventories, $\bar{P}^{\text{CF}}(t)$ the economy-wide capital formation price index, $K_i(t)$ the capital stock, and $L_i(t)$ the overall debt.

Insolvency:

$$L_i(t+1) = \zeta^{\text{b}}\, \bar{P}_i^{\text{CF}}(t) K_i(t) \tag{10}$$

$$D_i(t+1) = 0 \tag{11}$$

where ζ^{b} is a fraction of the remaining liabilities of its real capital stock for firm i, and $L_i(t+1)$ are liabilities of firm i and $D_i(t+1)$ are the deposits in the next period $(t+1)$.

Households

Activity Status:

$$w_h(t) = \begin{cases} \theta^{\text{UB}}\, w_h(t-1) & \text{if newly unemployed,} \\ w_i(t) & \text{if newly employed by firm } i, \\ w_h(t-1) & \text{if unemployment continues.} \end{cases} \tag{12}$$

An economically inactive person h receives social benefits $\text{sb}^{\text{inact}}(t)$ and does not look for a job:

$$\text{sb}^{\text{inact}}(t) = \text{sb}^{\text{inact}}(t-1)(1+\gamma^e(t)) \tag{13}$$

Consumption:

$$C_h(t) = \begin{cases} \sum_g C^d_{hg}(t) & \text{if the consumer successfully realized the consumption plan,} \\ < \sum_g C^d_{hg}(t) > & \text{if all firms visited could not satisfy the consumer's demand,} \end{cases} \tag{14}$$

where $C^d_{hg}(t)$ is the consumption budget of the h-th household to purchase the g-th good.

Household Investment:

$$I_h(t) = \begin{cases} \sum_g I^d_{hg}(t) & \text{if the household successfully realized the investment plan,} \\ < \sum_g I^d_{hg}(t) > & \text{if all firms visited could not satisfy its demand,} \end{cases} \tag{15}$$

where $I^d_{hg}(t)$ is the investment demand by household h for product g net of taxes.

Income:

$$Y_h(t) = \begin{cases} (w_h(1-\tau^{\text{SIW}} - \tau^{\text{INC}}(1-\tau^{\text{SIW}})) + sb^{\text{other}}(t))\overline{P}^{HH}(t) & \text{if employed} \\ (w_h(t) + sb^{\text{other}}(t))\overline{P}^{HH}(t) & \text{if unemployed} \\ (sb^{\text{inact}}(t) + sb^{\text{other}}(t))\overline{P}^{HH}(t) & \text{if not economically active} \\ \theta^{\text{DIV}}(1-\tau^{\text{INC}})(1-\tau^{\text{FIRM}})\text{max}(0, \Pi_i(t)) + sb^{\text{other}}(t)\overline{P}^{HH}(t) & \text{if an investor} \\ \theta^{\text{DIV}}(1-\tau^{\text{INC}})(1-\tau^{\text{FIRM}})\text{max}(0, \Pi_k(t)) + sb^{\text{other}}(t)\overline{P}^{HH}(t) & \text{if a bank investor} \end{cases} \tag{16}$$

where $\text{sb}^{\text{other}}(t)$ is the additional social benefits (related to family and children, sickness, etc.) from the government, τ^{INC} is the income tax rate, τ^{SIW} is the rate of social insurance contributions to be paid by the employee, τ^{FIRM} is the corporate tax rate, θ^{DIV} is the dividend payout ratio, $\bar{P}^{\text{HH}}(t)$ is the consumer price index, and $\Pi_i(t)$ is the profit of firm i.

Savings:

$$
\begin{aligned}
D_h(t) = D_h(t-1) \\
&+ \overbrace{Y_h(t) - \left((1+\tau^{\text{VAT}})C_h(t) + (1+\tau^{\text{CF}})I_h(t)\right)}^{\text{Savings}} \\
&+ \overbrace{r(t)\,\text{min}(0, D_h(t-1))}^{\text{Interest payments}} \\
&+ \overbrace{\bar{r}(t)\,\text{max}(0, D_h(t-1))}^{\text{Interest received}}\,.
\end{aligned}
\tag{17}
$$

where $Y_h(t)$ is the current disposable income, $C_h(t)$ the realized consumption expenditure, $I_h(t)$ the realized investment in housing, $D_h(t-1)$ the h-th household's previous deposits, τ^{VAT} the value-added tax rate on consumption, and τ^{CF} the tax rate on investment goods.

The General Government

Government Consumption:

$$
C_j(t) = \begin{cases} \sum_g C^d_{jg}(t) & \text{if the government successfully realized the consumption plan,} \\ < \sum_g C^d_{jg}(t) > & \text{if all firms visited could not satisfy its demand,} \end{cases}
\tag{18}
$$

where $C^d_{jg}(t)$ is the consumption budget of the j-th government entity to purchase the g-th good.

Government Revenues:

$$
\begin{aligned}
Y^G(t) = {} & \overbrace{(\tau^{SIF} + \tau^{SIW})\bar{P}^{HH}(t) \sum_{h \in H^E(t)} w_h(t)}^{\text{Social security contributions}} \\
& + \overbrace{\tau^{INC}(1 - \tau^{SIW})\bar{P}^{HH}(t) \sum_{h \in H^E(t)} w_h(t)}^{\text{Labor income taxes}} \\
& + \overbrace{\tau^{VAT} \sum_h C_h(t)}^{\text{Value added taxes}} \\
& + \overbrace{\tau^{INC}(1 - \tau^{FIRM})\theta^{DIV} \left(\sum_i \max(0, \Pi_i(t)) + \max(0, \Pi_k(t)) \right)}^{\text{Capital income taxes}} \\
& + \overbrace{\tau^{FIRM} \left(\sum_i \max(0, \Pi_i(t)) + \max(0, \Pi_k(t)) \right)}^{\text{Corporate income taxes}} \\
& + \overbrace{\tau^{CF} \sum_h I_h(t)}^{\text{Taxes on capital formation}} \\
& + \overbrace{\sum_i \tau_i^Y P_i(t) Y_i(t)}^{\text{Net taxes/subsidies on products}} \\
& + \overbrace{\sum_i \tau_i^K P_i(t) Y_i(t)}^{\text{Net taxes/subsidies on production}} \\
& + \overbrace{\tau^{EXPORT} \sum_l C_l(t)}^{\text{Export taxes}} .
\end{aligned}
\tag{19}
$$

where τ_i^Y and τ_i^K are the net rates on products and production, respectively.

Government deficit:

$$\Pi^G(t) = \overbrace{\sum_{h\in H^{inact}} \bar{P}^{HH}(t) sb^{inact}(t) + \sum_{h\in H^U(t)} \bar{P}^{HH}(t) w_h(t) + \sum_h \bar{P}^{HH}(t) sb^{other}(t)}^{\text{Social benefits and transfers}}$$
$$+ \overbrace{\sum_j C_j(t)}^{\text{Government consumption}}$$
$$+ \overbrace{r^G L^G(t-1)}^{\text{Interest payments}}$$
$$- \overbrace{Y^G(t)}^{\text{Government revenues}} \quad . \tag{20}$$

Government Debt:

$$L^G(t) = L^G(t-1) + \Pi^G(t) \tag{21}$$

where $L^G(t-1)$ are loans taken out by the government at the previous stage, and $\Pi^G(t)$ are year-to-year deficits/surpluses of the government.

The Bank

Provision of Loans:

$$\Delta L_i(t) = \text{max}\Bigg(0, \text{min}\Big(\Delta L_i^d(t), \zeta^{LTV} \bar{P}^{CF}(t-1)(1+\pi^e(t))K_i^e(t) - (1-\theta)L_i(t-1), \frac{E_k(t-1)}{\zeta} - \sum_{i=1}^{I}(L_i(t-1) + \Delta L_i(t))\Big)\Bigg) \tag{22}$$

where $E_k(t-1)$ is the equity capital (common equity) of the bank at time $t-1$, and $0 < \zeta < 1$ can be interpreted as a minimum capital requirement coefficient (i.e., $1/\zeta$ is the maximum allowable leverage for the bank), $\Delta L_i(t)$ is the realized amount of new loans to firm i in period t. Here, ζ^{LTV} is the loan-to-value ratio, and $K_i^e(t)$ is the expected value of firm i's capital stock; $\pi^e(t)$ is the expected inflation rate.

Accounting for Profits and Losses:

$$D_k(t) = \sum_{i=1}^{I} D_i(t) + \sum_{h=1}^{H} D_h(t) + E_k(t) - \sum_{i=1}^{I} L_i(t) \tag{23}$$

where $D_k(t)$ is the bank's balance sheet, $E_k(t)$ is the bank equity, $D_i(t)$ and $D_h(t)$ are the deposits from firm i and household h, respectively; $L_i(t)$ is the loan issued to firm i.

The Central Bank

Determination of Interest Rates:

$$\bar{r}(t) = \text{max}\left(r^* + \rho(\gamma^e - \gamma^*) + (1-\rho) * (\pi^e - \pi^*)), \bar{r}_{min}\right) \tag{24}$$

where ρ is a measure of weight assigned, r^* is the real equilibrium interest rate, π^* is the inflation target by the CB, γ^e is the expected economic growth and γ^* is the target economic growth. The CB policy rate follows Taylor Rule.

Accounting for Profits and Losses:

The central bank's profits $\Pi^{CB}(t)$ are:

$$\Pi^{CB}(t) = r^G L^G(t-1) - \bar{r}(t) D_k(t-1) \tag{24}$$

where $r^G L^G(t-1)$ are revenues from interest payments on government debt, and $\bar{r}(t)D_k(t-1)$ is the net position in advances/reserves with regards to the banking system.

The central bank's equity $E^{CB}(t)$ evolves according to its profits or losses and its past equity, and is given by:

$$E^{CB}(t) = E^{CB}(t-1) + \Pi^{CB}(t). \tag{25}$$

Net Creditor/Debtor Position of the National Economy:

The net creditor/debtor position of the national economy to the rest of the world $D^{RoW}(t)$ evolves according to the following law of motion

$$D^{RoW}(t) = D^{RoW}(t-1) - \underbrace{(1+\tau^{EXPORT})\sum_l C_l(t)}_{\text{Exports}} + \underbrace{\sum_m P_m(t)Q_m(t)}_{\text{Imports}} \tag{26}$$

where $C_l(t)$ is the realized consumption by foreign consumers, and $P_m(t)$ and $Q_m(t)$ are the prices and sales of imports, respectively.

Imports and Exports

Imports:

The total amount of imports $Y^I(t)$:

$$\text{log}(Y^I(t)) = \alpha^I \,\text{log}(Y^I(t-1)) + \beta^I \tag{27}$$

which is assumed to follow an AR(1) process.

The prices for these import goods are:

$$P_m(t) = \bar{P}_g(t-1)(1+\pi^e(t)) \tag{26}$$

where m produces the principal product g, $\bar{P}_g(t)$ is the product price index, and $\pi^e(t)$ is the expected inflation rate. This corresponds to the assumption of a fixed relation between the domestic and international price level, i.e., the same inflation rate at home and abroad.

Sales of imports are:

$$Q_m(t) = \min(Y_m(t), Q_m^d(t)) \tag{27}$$

where $Q_m^d(t)$ is the demand by consumers for foreign firm m.

Exports:

$$C_l(t) = \begin{cases} \sum_g C_{lg}^d(t) & \text{if the foreign consumer successfully realized the consumption plan,} \\ < \sum_g C_{lg}^d(t) > & \text{if all firms visited could not satisfy its demand,} \end{cases} \tag{28}$$

where $C_{lg}^d(t)$ is the demand for exported goods by the l-th foreign consumer to purchase the g-th good.

6.3 Market Risk Model Methodologies

6.3.1 Equities Indices - Fama French 5 Factor Model:

Market Risk Factors Modelled: Nikkei 225, FTSE 100 and S&P 500 equity indices

The Fama French five-factor model[11]builds upon the Capital Asset Pricing Model (CAPM) by adding values for size, value, profitability and investment to the existing market return over the risk-free rate. It predicts the expected returns of an asset based on the performance of each of the five factors (firm size, book-to-market value, excess return, profitability and investment), using parameters that are fitted to historical data. It was proposed in 2014 and it is an extension of the Fama French three factor model. This is used for equity indices: namely the NIKKEI 225, FTSE 100 and S&P 500. To calculate the market risk shocks for equity indices, the central bank's policy rate from the ABM is used as the risk-free rate to generate forward yield curves. The central bank policy rate in the ABM is driven by a policy rule which is a function of output and inflation. The values for each of the five factors are taken for the relevant equities from Kenneth French's online repository [12] , with the risk-free rate used to vary the market return factor. The returns are compared across different scenarios to generate the market risk factors for equity indices.

6.3.2 Sectoral Equity for the EU– Residual Income Method:

Market Risk Factors Modelled: EU sector shocks for electricity, manufacturing of chemical products, air transport, land transport, mining and quarrying and publishing activities Equity indices are created for firms in each sector of the economy, within the macroeconomic ABM [13]. At each time step, a basket of firms for each sector in the economy is valued and the ag-

[11]Fama, Eugene F., French, Kenneth R. Common risk factors in the return on stocks and bonds www.bauer.uh.edu/rsusmel/phd/Fama-French_JFE93.pdf

[12]French, Kenneth R. Developed Markets Factors and Returns https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[13]To create the index, the ten largest firms in each sector are chosen before the simulation begins. If fewer than ten firms are available in a sector, then all available firms are included. At each subsequent monthly timestep in the ABM, the firms are valued and the aggregate figure for each sector recorded. Note that these indices do not influence the agents within the ABM (eg, for investment decisions); they are only an output used to infer how real equity values might vary in response to climate shocks

gregate figure tracked over time. This method is used for the EU, as a developed economy with highly granular sectors. These sectors included Electricity, Manufacturing of Chemical Products, Air transport, Land transport, Mining and Quarrying. Publishing activities was included as a non-carbon intensive control sector. By comparing the change in the values of these firms between different climate scenarios, the effect of different shocks on equity values can be inferred. The firms are valued using a simplified version of the Residual Income Method (RIM), which considers firm fundamentals: income, assets and liabilities. A full description of the model is provided in the appendix. The total profits that a firm expects to make over the next ten-year period– less the expected return on equity capital – are discounted and added to the present book value of the firm. The expected profits for future time steps over ten years are assumed to be equal to the profit at the current time step – i.e. each firm performs identically for each subsequent time step. Therefore, instantaneous changes to the business environment like the imposition of a carbon tax (which reduce net margin) have an immediate impact on the value of firms. The book value of a firm is taken to be its assets, net of liabilities. Assets are the sum of total fixed capital, stock of intermediate and finished goods, plus cash at hand. Liabilities are debts owed to the commercial bank. All values of assets and liabilities are taken from the existing balance sheet of each individual firm, a description of which is provided within the ABM section of the appendix.

6.3.3 Credit Default Swaps (CDS) - ISDA Market Standard Bootstrapping CDS Spreads:

Market Risk Factors Modelled: USD CDS on UK

A Credit Default Swap (CDS) is a derivative product used for trading and risk management. Here, a USD-denominated CDS on UK government debt is modelled. Credit events can include complete default on payments, partial default, credit rating downgrades, or widening credit spreads. To analyze a credit event, the Poisson process is often used which is a probabilistic model. The Poisson process estimates the probability of default between two-time intervals, conditional on survival until the initial time point. Hazard rates, or default intensities, are used in the Poisson process to model the likelihood of a credit event occurring. Similarly, survival probability is a fundamental factor in pricing CDS contracts. It is the probability that no credit event will occur, and it is the complement of the probability of default. Survival probability is not directly observable and must be implied from traded credit spreads in the market. A bootstrapping algorithm is used to calculate survival probabilities from traded CDS spreads. The CDS spreads represent the market's view of credit risk. By using these spreads, the algorithm derives the survival probabilities, assuming a constant recovery rate of 40% [14], to price the CDS contracts. The discount factors for the bootstrapping algorithm are derived from the yield curve model which generates rates for the respective time frames. These are fed back into the bootstrapping algorithm to price the CDS contracts.

6.3.4 Yield Curves – Hull White One-factor Model:

Market Risk Factors Modelled: The 1D, 6M, 1Y, 5Y,10Y and 20Y government bond yields for GBP, Germany (as a proxy for Europe), USD, Brazil and India

[14] ECB 2006 Financial Stability Review. ISSN 1830-2025, European Central Bank, 2006, p. 80 www.ecb.europa.eu/pub/pdf/fsr/financialstabilityreview200612en.pdf

A Hull White one factor model is used to derive yield curves. It is an extension of the Vasicek model [15] , with the ability to fit a term structure of interest rates. It assumes that short-term interest rates follow a mean-reverting stochastic process. The model is used to simulate many different paths of future interest rates based on a varying short rate, here taken to be the risk-free rate from the macroeconomic ABM. The future path of interest rates is modelled using two parameters that are calibrated to historical data: the speed of mean reversion and the volatility of the short rate. The volatility of the short rate is calculated directly from historical data [16] from each economy modelled in the ABM. The speed of mean reversion is calculated using a least-squares fitting to historical yield curves – determining the value that best replicates past data. This ensures that the dynamics of the interest rates conform to historical expectations (including previous financial crises). However, it does not necessarily limit the magnitude of the shocks to historical precedent. For each monthly time step in the macroeconomic ABM, the policy rate is used to calculate different paths of interest rates. The pre-determined values for the speed of mean reversion and volatility are used throughout, for their relevant economies. From these, a yield curve is constructed which best fits the future paths of interest rates. By comparing these across different scenarios, the shocks to yield curves that result from the physical, transition and combined risks are determined.

6.3.5 Interest Rate Swaps – PCA-based Machine Learning:

Market Risk Factors Modelled: The 1D, 6M, 1Y, 5Y,10Y and 20Y swap curve for GBP, EUR and USD

Interest rate swap curves are modelled here using a combination of Principal Component Analysis (PCA) and machine learning, relating changes in the predicted yield curves for a particular economy to changes in swap spreads [17]. Yield curves are generated for each economy modelled by the macroeconomic ABM using the Hull White One Factor Model (see above). The difference between these yield curves and those from the reference date of the simulation, 30th June 2023, are then calculated at each time step. These differences are then decomposed into their PCA components and the regressor used to predict the changes in the swap curve with respect to the reference date. Adding the changes in the swap spreads to the changes in the yield curve – from the Hull White model – allows the overall changes in the swap curves to be determined for each scenario. The changes in swap curves are then compared between scenarios to generate the swap curve market risk shocks [18].

6.3.6 Foreign Exchange (FX) – Purchasing Parity Power Model:

Market Risk Factors Modelled: USDINR, USDJPY, USDEUR, USDGDP, USDBRL

[15] Hull, J., White, A. The Journal of Financial and Quantitative Analysis. Vol.28, No 2 (June1993)

[16] Data used for short rate volatility: Brazil, daily from 06/10/03 – 30/06/23; EU, daily from 06/10/03 – 30/06/23; India, daily from 03/04/2009 – 30/06/23; Japan, daily from 16/02/2016 – 30/06/23; UK, daily from 02/01/18 – 30/06/23; US, daily from 08/01/71 – 30/06/23

[17] The shape of the yield curve can be parameterised using PCA, with the first three components often used to infer economic conditions or expectations. It has been shown that a relationship exists between swap spreads and PCA components of benchmark yield curves

[18] For training of the machine learning model, week-to-week changes in historical yield and swap curves are calculated and PCA performed on these yield curve deltas. A Random Forest regressor is trained to predict the changes in swap spreads from the first three components of the yield curve delta PCA

To forecast currency exchange rates, the Purchasing Power Parity (PPP) based approach is used, which combines the macroeconomic outputs produced by the ABM and combining it with machine learning model, XGBoost, which is based on a study by Amat et al. in 2018. The methodology is based on the assumption that exchange rates should adjust so that the same basket of goods costs the same in different countries, considering purchasing power. For each currency pair, the changes in GDP, inflation and risk-free rates for each country are used as the independent variables for an XGBoost regression model. XGBoost is chosen for its efficiency and features that help prevent making predictions that are too specific to the historical data (overfitting).. This model learns from past data about how exchange rates have changed. Finally, the economic factors predicted by our ABM model are used to forecast how exchange rates will change for specific pairs of currencies.

6.3.7 Commodities – Macroeconomic Regression:

Market Risk Factors Modelled: Gold, CBOT Corn, Coal Price and WTI Crude

A machine learning-based approach is used to predict commodity prices based on historical relationships with economic output. Commodity price predictability has been shown to be closely linked to the economic cycle10 with this relationship strongest in periods of economic recession. Here, a Random Forest [19] regressor is trained on the relationship between the GDP of the developed economies modelled by the macroeconomic ABM and historical commodity prices. A Random Forest regressor is chosen over a linear or polynomial-based approach to capture the non-linearities inherent in the macroeconomic-commodity price relationship. Commodity prices are taken at quarterly intervals to match the frequency of the macroeconomic data between 2000-2022 inclusive. When regressing commodity prices on macroeconomic variables, out-of-sample predictability has been shown to be greatest for a quarterly horizon [20] . For the short-term horizons considered here, historical correlations are assumed to hold as traders and consumers utilize existing schemas and/or models to drive behavior. Longer term horizons may consider basing regression on more fundamental variables related to specific economic sectors. The trained regressor is then used to predict commodity prices using the values of GDP predicted by the ABM. Values of GDP for the US, UK, EU and Japan are used as input to the regressor to forecast the commodity prices at each monthly timestep.

6.3.8 Retail Mortgage-Backed Securities (RMBS) – Richard and Roll Prepayment Model:

Market Risk Factors Modelled: The USD RMBS

To value residential mortgage-backed securities, the Richard and Roll prepayment model is used. Developed by Dwight J. Richard and Richard R. Roll, it is widely used for modelling mortgage-backed securities (MBS) and Collateralized Mortgage Obligations (CMOs). It estimates the prepayment rates of borrowers in a pool of mortgages, which is crucial for assess-

[19] Random forests are a scheme proposed by Leo Breiman in the 2000's for building a predictor ensemble with a set of decision trees that grow in randomly selected subspaces of data. www.jmlr.org/papers/volume13/biau12a/biau12a.pdf

[20] Gargano, Antonio, and Allan Timmermann. "Forecasting Commodity Price Indexes Using Macroeconomic and Financial Predictors." International Journal of Forecasting, vol. 30, no. 3, July 2014, pp. 825–43. ScienceDirect, https://doi.org/10.1016/j.ijforecast.2013.09.003.

ing the performance, value and risk of mortgage-related securities. Defaults are accounted for using the Standard Default Assumption (SDA), which assumes a default rate that changes over time. A detailed explanation of the Richard and Roll prepayment model is provided in the Appendix B. The model works on the assumption that mortgagors can and will refinance their loans if it is economically rational to do so. This is crucial to determine the value of the security, because it relies heavily on the sum of future discounted cash flows paid by the mortgagors. Key macroeconomic and market risk variables used to assess refinancing feasibility includes, policy rates, the effects of mortgage seasoning and seasonality, credit spreads and premium burnout. The model frames the decision to prepay/refinance a mortgage as an American-style option, with a strike price that is equal to the sum of the outstanding principal and the refinancing costs. This naturally depends on the future path of interest rates, which here is forecast using the Cox-Ingersoll-Ross (CIR) model. Once the prepayment rates have been determined, the future cash flows are calculated for all tranches of the security. When discounted, they form the present value of the RMBS which can be compared across different scenarios. Here, a Monte Carlo simulation is run to estimate the yield of a sample CMO with five tranches. The simulation involves generating mortgage rates, prepayment rates, default rates, and cash flows, then distributing them according to the CMO's structure. Simulation Results are obtained after 10,000 simulations, the yields and weighted average lives (WALs) of the tranches are calculated, providing insights into the expected returns and maturities of each tranche.

6.3.9 Realized Volatility:

Market Risk Factors Modelled: Equity, FX, Interest rates and commodity volatilities

The approach follows the Zhu et el (2023) methodology which is a panel data-based machine learning approach (PDML) employed to forecast the realized volatility. They forecast realized volatility using panel data where the cross-sectional realized volatilities are computed with high frequency data, using a two-stage framework. At first, an optimal window size from an initial set of available choices is selected, the model is then trained using the optimal window size. The results of the PDML approach demonstrate superior performance compared to classical linear models and can be embedded into any machine learning model, making it flexible for practical applications.

6.3.10 Probability of Default:

Market Risk Factors Modelled: USD CDS on UK 1Y and 5Y implied PD

To forecast probabilities of default, an advanced machine learning based model is used, that builds upon the Merton model, based on the work of Mao et al. in 2023.The model uses a type of machine learning model called Long Short-Term Memory (LSTM) to analyze the connection between certain financial indicators and macroeconomic variables (i.e., risk free rate) and Credit Default Swap (CDS) spreads. Unlike many other methods that categorize companies as either normal or in default, this approach embraces the complexity of the data. The LSTM's ability to understand complex relationships in the data significantly improves the accuracy of the forecasts.

6.4 Emerging Markets: Regression of Macroeconomic Variables

In the study of global economic interdependencies, a structured approach is taken to investigate the influence of developed markets on emerging markets. Utilizing the data generated by the macroeconomic agent-based model (ABM), a series of regressions are conducted to understand the relationships between key macroeconomic variables.

Each variable in the emerging markets is individually regressed on its counterpart from the developed markets using a Random Forest regressor. This non-linear regression technique is well-suited for capturing intricate dependencies and interactions between variables, especially given the complex nature of global economic dynamics.

The set of macroeconomic variables under consideration includes:

- Gross Domestic Product (GDP)
- Inflation
- Total Household Consumption
- Central Bank Interest Rate
- Total Investment (spanning both firms and households)
- Government Consumption
- Imports

For each variable, a separate Random Forest regression object is trained. For example, the GDP of the emerging market is regressed on the GDP of the developed markets, the inflation rate in the emerging market on the inflation rate in the developed markets, and so on. The data is first scaled using a Min-Max scaler, whilst the regressor has a maximum of 300 estimators and a maximum depth of 5. Quarterly macroeconomic data are used for training, which are linearly interpolated and scaled to monthly values to match the monthly timestep of the ABM. Training data is taken from between 2000-2022 inclusive.

$$
\begin{aligned}
\text{GDP}_{\text{emerging}} &= f_1(\text{GDP}_{\text{developed}}) \\
\text{Inflation}_{\text{emerging}} &= f_2(\text{Inflation}_{\text{developed}}) \\
&\vdots
\end{aligned}
$$

Where each f_i represents a distinct Random Forest regressor for the i^{th} macroeconomic variable.

By training these models on historical data, it becomes possible to predict the macroeconomic performance of emerging markets based on the projected values of the developed markets, as forecasted by the ABM. This approach offers a nuanced understanding of how macroeconomic changes in developed economies can cascade and impact the economic landscapes of emerging markets.

6.5 Model Data

The data used in the models is described below and is split by region.

Europe

Data sources include micro and macro data from national accounts, sector accounts, input-output tables, government statistics, census data, and business demography data and are collected for the latest available data as at 30th June 2023 from Eurostat6. Model parameters, used as input to the macroeconomic model, are either taken directly from data or calculated from national accounting identities. Parameters that specify the number and type of market participants are taken directly from census and business demography data.

Model parameters concerning productivity and technology coefficients, as well as capital formation and consumption coefficients, are taken directly from input-output tables, or are derived from them. Tax rates and marginal propensities to consume or invest are calculated from national accounting identities. These rates are set such that the financial flows observed in input-output tables, government statistics, and sector accounts are matched. Capital ratios and the inflation target of the monetary authority are set according to the literature7. For exogenous processes such as imports and exports, parameters are estimated from the Eurostat national accounts (main aggregates).

UK

Data for the UK has been largely sourced from the Office for National Statistics8 (ONS) for the latest available date. The data has largely been taken from UK input-output tables, national accounts, government statistics, census data and business demography data. Data that specify the number and type of market participants are taken directly from census and business demography data.

The model parameters concerning productivity and technology coefficients, as well as capital formation and consumption coefficients, are taken directly from input-output tables, or are derived from them. Tax rates and marginal propensities to consume or invest are calculated from national accounting identities.

Japan

Data for the Japanese economy has largely been sourced from the e-Stat9 which a portal site for official statistics of Japan. The dataset comprises of Japanese government deficit and revenue, input-output tables, census data, business demography data and national accounts data. Capital formation, technology and productivity coefficients are sourced from the input output table directly or calculated from the tables.

US

Data for US economy has been sourced from Bureau of Economic Analysis10 which is provided by the US Department of Commerce. Data obtained included: GDP by industry, input-output tables, income, and employment by industry, savings and investment data. Like the other advanced economies being modelled, the tax rates and marginal propensities to consume or invest are further calculated from national accounting identities. Model parameters concerning productivity and technology coefficients, as well as capital formation and consumption coefficients, are taken directly from input-output tables, or are derived from them as in the methodology shared by Polenda et al (2019).

6.6 Scenario Expansion

6.6.1 Yield Curve Model

The one-factor Hull-White model models future yield curves at every time step of the macroeconomic ABM, where central bank policy rate acts as a short rate. The stochastic differential equation defining the Hull-White model for the short rate $r(t)$ is given by:

$$dr(t) = (\theta(t) - ar(t))dt + \sigma dW(t)$$

In this equation, $\theta(t)$ ensures consistency with the initial yield curve, a represents the speed of reversion, σ is the volatility parameter, and $W(t)$ denotes a Wiener process.

To calibrate the Hull-White model, historical data is employed to estimate the parameters a and σ. The speed of reversion, a, is determined by analyzing how quickly interest rates revert to their long-term average, while the volatility parameter, σ, is calculated based on the observed variability of interest rate changes over time. These calibrated parameters are instrumental in capturing the historical behavior of interest rates and ensuring that the model accurately reflects the underlying market dynamics.

With the policy rate set by the central bank agent at each timestep, the Hull-White model utilizes the calibrated parameters to forecast the short rate and, by extension, the entire yield curve at the subsequent timestep. This iterative process results in a series of predicted yield curves, aligning with the central bank's policy decisions and providing a dynamic view of potential future interest rate movements.

This modelling approach, therefore, not only aids in understanding the impact of monetary policy on yield curves but also ensures that the predictions are grounded in historical market behavior, enhancing the reliability of the forecasts.

6.6.2 Sectoral Equity Model

Equity indices are created for firms in each sector of the economy, within the macroeconomic ABM. This method is used where the economies are partitioned into a large number of sectors, for example the EU. The value of each firm is calculated at the first time step according to a simplified version of the Residual Income Method (RIM), Equation 29:

$$V_0 = BV_0 + \sum_{i=1}^{n} \frac{RI_i}{(1+r)^i} \tag{29}$$

Where BV_0 is the present book value of the firm, r is the expected rate of return on equity capital and RI_i is the residual income for the i^{th} period. The residual income is calculated as the firm's profit less the expected return on equity capital, $RI_i = r\, BV_0$. The expected rate of return on equity capital is the current risk free rate set by the Central Bank in the ABM, plus the fixed risk premium used by the Bank agent to determine loan repayments. The book value of the firm BV_0 is calculated as net assets less liabilities, with values for deposits held at the bank, stock of finished goods, fixed capital and outstanding loans taken from the balance sheets of individual firms within the ABM. Firm profits for the i^{th} step are assumed to be the same as the profit for the current step, discounted by the current expected rate of return compounded for the i^{th} period. The residual income is calculated over a number of periods equivalent to 10 years. Up to the 10 largest firms in each sector at the first time step are tracked throughout the remainder of the ABM simulation. An index, initially set to unity, is formed that tracks their value. The industry specific impact of the scenario is hence captured through the firm profits which is captured by the present book value of the firm.

6.6.3 Fama French Five Factor Model - Equity Indices

The Fama French five-factor model builds upon the Capital Asset Pricing Model (CAPM) by adding values for size, value, profitability and investment. It predicts the expected returns of an asset based on the performance of each of the five factors, using parameters that are fitted to historical data. It was proposed in 2014 and it is an extension of the Fama French three factor model. This is used specifically for equity indices: namely the NIKKEI 225, FTSE 100 and S&P 500. The model is as follows:

$$R = \alpha + \beta_{\mathrm{m}} MKT + \beta_{\mathrm{s}} SMB + \beta_{\mathrm{h}} HML + \beta_{\mathrm{r}} RMW + \beta_{\mathrm{c}} CMA \tag{30}$$

Where MKT is the market risk premium, SMB is the return on a diversified portfolio of small cap stocks minus the return on a diversified portfolio of big cap stocks, HML is the difference between the returns on diversified portfolios of stocks with high and low book to market ratios, RMW is the difference between the returns on diversified portfolios of stocks with robust and weak profitability and CMA is the difference between the returns on diversified portfolio of stocks of low and high reinvestment ratios investment firms. The coefficients α, β_{m}, β_{s}, β_{h}, β_{r} and β_{c} are respectively: the excess return over benchmark; sensitivity to market risk; sensitivity to size factor; sensitivity to value factor; sensitivity to profitability factor; and sensitivity to investment factor. The five factors are derived from the historical data from Kenneth R French data library. To calculate the market risk shocks for equity, the central bank's policy rate is factored into the MKT parameter of the Fama French 5 factor model. The central bank policy rate is an output from the Agent Based Macroeconomic (ABM) model.

6.6.4 Interest Rate Swaps Model

The methodology developed for modelling swap spreads employs Principal Component Analysis (PCA) to analyse changes in the yield curves. The yield curves used are those predicted by the Hull-White One Factor model described in Section . The relationship between the first to third principal components of the yield curve PCA and swap spreads is utilized, drawing on insights from Moody's Analytics (Licari et al. (2013)) and the Bank of England Quarterly Bulletin (Cortes (2006)).
Changes in both yield curves and swap spreads are calculated at weekly intervals over a 10 year period, denoted as $\Delta Y(t)$ and $\Delta S(t)$ respectively, where t represents the time index.

$$\Delta Y(t) = Y(t) - Y(t-1) \tag{31}$$

$$\Delta S(t) = S(t) - S(t-1) \tag{32}$$

Here, $Y(t)$ and $S(t)$ represent the yield curve and swap spread at time t, respectively.

Following the calculation of changes, Principal Component Analysis (PCA) is applied to the yield curve changes, resulting in a set of principal components $PC_i(t)$, where i ranges from 1 to 3. This transformation captures the main patterns of variation in the yield curve changes.

$$\begin{bmatrix} PC_1(t) \\ PC_2(t) \\ PC_3(t) \end{bmatrix} = \text{PCA}\left(\Delta Y(t)\right) \tag{33}$$

Subsequently, a regression model, specifically a Random Forest algorithm, is employed to establish a relationship between the principal components of the yield curve changes and the changes in swap spreads. This is expressed as:

$$\Delta S(t) = f(PC_1(t), PC_2(t), PC_3(t)) \tag{34}$$

The coefficients of this regression model encapsulate the sensitivity of swap spread changes to changes in the yield curve, as represented by the principal components.

Finally, for a given yield curve, the methodology enables the prediction of swap spread changes, which can then be added to the known swap spreads from a reference date, such as June 30th, 2023. This results in a comprehensive model that provides insights into the relationship between yield curves and swap spreads, and facilitates the prediction of swap spread movements based on changes in yield curves.

6.6.5 Commodities

A machine learning-based method is used to forecast commodity prices, specifically employing a Random Forest regressor. This model establishes a relationship between the prices of commodities and the Gross Domestic Product (GDP) of key developed economies modelled by the ABM: the United Kingdom, the United States, Japan, and the European Union.

The training process involves using historical data, wherein the commodity prices serve as the dependent variable, and the GDP values of the specified developed economies act as the independent variables. Quarterly GDP figures are used from between 2000-2022 inclusive. The average commodity price over each quarter is used for the regression. The Random Forest algorithm, known for its capability to handle non-linear relationships and interactions between variables, is then trained on this dataset. A maximum of 300 estimators are used with a maximum depth of 5. For each GDP output of the macroeconomic ABM, at monthly intervals, the commodity prices are then predicted. This approach relies on historical correlations between different commodities and GDP holding in each climate scenario. It is assumed that these correlations are robust for the short liquidity horizons considered here (less than one year), due to the pre-existing models and schemas that would govern market dynamics over the short term.

6.6.6 RMBS - Richard and Roll Prepayment Model

The Richard and Roll prepayment model assumes that prepayment rates are dependent on four factors:

Refinancing Incentive (RI):

- RI measures the financial motivation for borrowers to refinance their mortgages. It's based on the difference between the current interest rate on their mortgages (C) and the prevailing market interest rate for new mortgages (R).
- The larger the gap between C and R, the greater the incentive for borrowers to refinance. If C is much higher than R, borrowers can save money by refinancing.
- The relationship between C and R is typically nonlinear, and various functions can be used to represent this relationship.

Seasoning Multiplier (SM):

- This factor accounts for the observation that prepayments tend to increase as mortgages age or "season." As mortgages get older, borrowers are more likely to refinance or prepay.
- The model incorporates a seasoning factor that increases prepayment rates as time progresses. It is assumed that the peak of the prepayments occurs in the 30th month:

$$SM_t = \text{min}\left(\frac{t}{30}, 1\right) \tag{35}$$

Month of the Year:

- The model considers that prepayments occur more frequently during certain months of the year. Borrowers may be more likely to refinance in the summer or early autumn compared to winter.

- The model uses values for each month to adjust prepayment rates, with some months having higher prepayment probabilities than others.

Burnout Multiplier (BM):

- This factor accounts for the declining propensity of borrowers to prepay their mortgages over time. For example, a change in a borrower's credit status may make their loan ineligible for refinancing.
- The burnout multiplier captures the diminishing likelihood of prepayment as the outstanding balance of the mortgage pool decreases.

The annualized Conditional Prepayment Rate (CPR) is a product of all four factors:

$$CPR_t = RI_t \times SM_t \times MM \times BM_t \tag{36}$$

Modelling Interest Rate Paths:

The Cox-Ingersoll-Ross (CIR) model is essentially a model is used to model the movements in the interest rate. It is a one-factor model, predicting the movements in the interest rate driven by market risk. The governing equation is:

$$dr_{\mathrm{t}} = a(b - r_{\mathrm{t}})dt + \sigma\sqrt{r_{\mathrm{t}}}dW_{\mathrm{t}} \tag{37}$$

where r_{t} is the short-term interest rate, b is the long-term mean, a is the speed of mean reversion and σ is the volatility.

Interest rates are modelled using the Cox-Ingersoll-Ross (CIR) short-term rate process, with parameters calibrated to historical data. The Cox-Ingersoll-Ross short term interest rate process is:

$$dr_t = a(b - r_t)dt + \sigma\sqrt{(r_t)}dW_t \tag{38}$$

Parameter 'b' is a long-term mean and 'a' is a speed of adjustment to the mean. Sigma represents standard deviation and 'Wt' is a Brownian motion.

One of the main advantages of the CIR model is that it is able to capture the mean reversion property of interest rates, which is a well-documented phenomenon in financial markets. Mean reversion refers to the tendency of interest rates to move back towards their long-term average over time. The CIR model also has the advantage of being able to produce positive interest rates, which is important for the financial models. This is achieved by constraining the short rate to be non-negative, which is a desirable feature when modelling interest rates.

6.6.7 Forecasting Foreign Exchange Rates

Model Selection

It is generally agreed among macroeconomists that using economic relationships such as uncovered interest parity (UIP) to predict exchange rate movements has resulted in poor prediction results, despite such models being well-grounded theoretically. An indentified and critically constraining factor of existing models is their functional form, in which, the forecasting equations are generally simple linear combinations of the fundamentals (such interest rates, inflation and GDP), thereby neglecting the potential impact of (generally acknowledged to be important) non-linearities. The reason for the strict linear form originates in the theoretical derivations of existing models such as purchasing power parity (PPP) and the monetary model (MM). However, it is also acknowledged that fundamentals play a significant role in forecasting the movement of exchange rates if a non-linear formulation is used. Following the suggestion of Amat et al. (2018), we opted to use a ML model XGBoost on the basis of generally superior forecasting performance as a result of capturing potential non-linearities and for the purposes of calibrating the key model parameters.

Based on Amat (2018), we opted to use XGBoost (eXtreme Gradient Boosting) which is a package developed by Chen and Guestrin (2016) for easy application and tuning of gradient boosting for classification and regression (we use XGBoostRegressor) for forecasting exchange rates. Gradient boosting is an ensemble method that combines the weighted predictions of multiple weak learners, in the form of trees, into a superior model for forecasting. The XGBoost model works by sequentially fitting weak learners to bootstrapped samples from the source data. Instead of fitting the samples to the target variable, the goal is to reduce the residuals of weak learners by successively reducing the residuals of the previously fitted weak learners. This is acheived by adding up the predictions of the weak learners and then minimizing the prediction error. When the error can no longer be reduced, the final additive regression model takes the following form:

$$\Delta\hat{y}_{t+1} = \sum_{k=1}^{K} f_k^r(x_t) \tag{39}$$

where f_k^r denotes the regression tree formulation of XGBoost and K is the number of weak learners in the final model. The model is fitted by minimizing a predefined loss function that includes a penalty term for regularization:

$$\text{Loss}_r(\Delta\hat{y}_{t+1}, \Delta y_{t+1}) = \sum_{k=1}^{K} k(\Delta\hat{y}_{t+1}, \Delta y_{t+1}) + \sum_{k+1}^{K} \Omega(f_k) \tag{40}$$

where the loss term $\Omega(f_k)$ is specified as follows:

$$\Omega(f_k) = \gamma M + \frac{1}{2}\lambda||\omega||^2 \tag{41}$$

and where M denotes the number of leaves in a weak learner and $||\omega||^2$ is the L^2 norm of the weights ω attached to each leaf in a tree. Following Chen and Guestrin (2016) the $\Omega(f_k)$ term penalizes both tree complexity and prevents unnecessarily large terms in the loss function.

6.6.8 Data

The monthly historical dataset used to train the model covered the period from January 1990 to June 2023 (a total of 396 observations for each currency pair). The data was sourced from the OECD, Reuters and the US Federal Reserve. For forecasting purposes, we appended monthly data for GDP, interest rates (domestic and foreign), inflation rates (domestic and foreign) produced from our agent-based macroeconomic model. When training complex machine learning models, it is important to provide the ML algorithm with sufficient observations to achieve an acceptable level of learning without over-fitting. So, for this reason, we opted to train the algorithms using the combined data of all currencies, but to make the out of sample (OOS) forecasts for each currency pair separately. All variables were scaled with maximum absolute scaling. To distinguish between countries, the IDs of the currency pairs were also encoded as dummy variables. The date information was also included as time dummies for months and years. For every country pair, the dataset was split into a training set (in-sample) containing the first 80% of the available periods and a validation set (out-of-sample) consisting of the remaining 20% of the periods. Following Pfahler (2022), we trained with and without fundamentals and therefore opted to include macroeconomic fundamentals in the XGBoost model for forecasting. Model hyper-parameters were tuned and validated for each currency pair using grid search and 5-fold cross-validation.

6.6.9 Forecasting Realised Volatility

Model Selection

Forecasting quantities such as asset prices is an extensively researched topic in finance. However, many empirical studies (Chen et al, 2020; Gu et al, 2020) have shown that consecutive asset returns are correlated very weakly and tend to behave similarly to the increments in a random walk, which generally leads to poor predictive ability. However, realized volatility, offers potential to explain the behavior of markets. Indeed, Brandt et al (2010) found a strong negative correlation between idiosyncratic volatility and future asset returns and the persistence of stylized facts such as volatility clustering, together imply that volatility is highly likely to be predictable. Bucci (2018) provides a thorough overview of volatility forecasting.

In classical linear setting, forecasting models use only a small subset of variables partly because these methods rely on linear regression which breaks down when a model contains too many explanatory variables that may be strongly correlated. Fortunately, rapid development of machine learning and its ability to capture inherent non-linearities in the relationships between variables has yielded considerable successful research, with much of it based on neural networks (NNs). NNs have been found to be helpful in forecasting volatile financial variables where the non-linear dependence is evident, for instance, in stock prices and interest rates. A variety of machine learning techniques have been employed in volatility prediction, such as Lasso, random forest and gradient boosting, etc. Techniques such as cross-validation provide greater flexibility when selecting the most efficient models.

The approach outlined in this document follows Zhu et al (2023) whose methodology (referred to as the panel-data-based machine learning approach, or PDML) we employed to forecast realized volatility. They forecast realized volatility using an ML model based on panel data where the cross-sectional realized volatilities are computed with high-frequency data using a two-stage framework.They first select an optimal window size from an initial set of available choices, then train their model using the optimal window size. The results of their PDML approach demonstrate superior performance compared to classical linear models and can be embedded into any ML model, making it very flexible for practical applications.

Time series models and panel models are often discussed separately. In the existing literature, there is a lack of comparison of their forecasting performance. For example, Fama and French (2020) compared cross-section and time-series factor models, considering size, value, profitability, investment, and momentum factors. Their focus was solely on which model could provide better descriptions of average returns. Unlike their orientation, our focus was selecting an ML model based on its predictive ability. Zhu et al (2023) find that their PDML model produces comparable performance to time-series models, but crucially, time-series models incur computational costs far greater than a panel-data-based model.

Based on the performance results reported by Zhu et al (2023) and on the flexibility and ease of use of ML techniques they evaluated, we opted to use stochastic gradient boosting (SGB) to fit the base learners form the training samples at each iteration. Gradient boosting is a greedy procedure because new decision trees are added to the model to correct the residual error of an existing model. Each decision tree is created using a search procedure that selects split points to best minimize an objective function. SGB incorporates randomization into the gradient boosting procedure by randomly selecting a subsample used to fit the base learners from the entire training sample at each iteration. The update to the model approximation is therefore also random in successive iterations. Specifically, in each iteration of SGB, a tree is grown from a random subset that is selected from the original data by sampling without replacement. Trees are added until the total residual deviance based on the held data does not decrease and finally reaches the most suitable prediction model.

There are three important hyper-parameters in SGB. Namely, the learning rate that determines the contribution of each tree to the whole model, tree complexity that determines the sample number in each final node and the number of trees. Following Zhu et al (2023) we set the learning rate to be either $\nu = 0.01$, 0.05 or 0.1, the maximum depth of each tree to vary between 1 and 10, whilst the number of trees K, is set to be either 50, 100, or 150, which coincides with the number of iterations. All hyper-parameters were tuned by random grid search and 5-fold cross-validation.

K weak learners in an SGB model implies that the algorithm iterates K times, each with a base learner, $h(X_T; \gamma_k)$ with parameter γ_k, such that the impact of a weak learner $f(X_T)$ is calculated by:

$$f(X_T) = h(X_T; \gamma_0) + \sum_{k=1}^{K} \eta_k h(X_T; \gamma_k) \tag{42}$$

where η_k is an expansion coefficient and $h(X_T; \gamma_0)$ is the initial learner. The k_{th} learner w as chosen at k_{th} iteration with the first $k - 1$ learners being fixed. The objective of the algorithm is to select a prediction function by minimizing the loss criteria, denoted by ϕ over the training data. Again, we follow Zhu et al (2023) and set ϕ as the root mean squared error function, which implies the following form for the optimal prediction function $f(X_T)$ fitted on T is given by:

$$f(X_T) = \text{argmin}_f \left(\sum_{j=1}^{W_B^*} \sum_{i=1}^{N} \phi(RV_{T-j+1}^{(i)}, f(X_{T-j}^{(i)})) \right) \tag{43}$$

Then, if $f(x)$ is a parameter, use gradient descent to get the solution. Let $f_{k-1}(X)$ represent the estimation of $f(X)$ at the $(k - 1)$st iteration. At the kth iteration, the algorithm randomly selects a subset from the original training dataset, in which samples being randomly selected are collected in set Υ_k. Following Zhu et al (2023) for convenience, define $(RV_{q,T+1}, X_{q,T})$ as the qth subsample from the entire training sample, as an equivalence to $\left(RV_{T-\tau+1}^{(q-\tau N)}, X_{T-\tau}^{(q-\tau N)}\right)$ for $\tau = \left[\frac{q}{N}\right]$ and $q = 1, ..., W_B \times N$. The negative gradient $\tilde{RV}_{j,T}$ is calculated by:

$$\tilde{RV}_{j,T} = -\frac{\partial f \phi(RV_{j,T}, f(X_{j,T}))}{\partial f(X_{j,T})} \tag{44}$$

γ_k is estimated by minimizing the sum of the squared error, so that η_k is found by minimizing the loss function:

$$\eta_k = \text{argmin}_\eta \sum_{j \in \Upsilon_k} \phi(RV_{j,T}, f_{k-1}(X_{j,T}) + \eta h(X_{j,T}; \gamma_k)) \tag{45}$$

The final step is to update the estimate at the kth iteration using:

$$fk(X) = f_{k-1}(X) + \nu \eta_k h(X; \gamma_k) \tag{46}$$

where ν is the shrinkage parameter. After K iterations the final model output is the result $f_K(X)$.

Data

We used 1 minute tick data from on-line sources and following Zhu et al (2023) we analyzed a series of high-frequency factors into panel models to assess their usefulness. By shrinking the large-scale macroeconomic variables with machine learning methods, we identified some significant stylized facts/features for use in forecasting future realised volatility. High-frequency features, such as the realized semi-covariances, realized skewness and realized kurtosis, all exhibited significance in forecasting volatility and were therefore used in estimation for the relevant asset class/instrument.

6.6.10 Modelling Probabilities of Default

Model Selection

Predicting corporate defaults plays a central role in each sector of the economy, as was highlighted during the global financial crisis of 2007-2010 and its accompanying increase in credit risk. There have been three broad types of statistical models: discriminant analysis (e.g. Mare et al 2017), binary response (e.g. Aretz et al 2018) and hazard (e.g. Traczynski et al 2017). More recently, machine learning methodologies such as support vector machines, decision trees and artificial neural networks have been brought to bear on the challenge of default prediction. Research has demonstrated that default prediction models should be multiperiod, such that future outcomes are affected by past decisions. It has also been demonstrated that stock price and corporate value (as determined by the stock market) are important factors to use in default prediction. It has been further highlighted that an extremely desirable feature of a corporate default prediction model should be the ability to suggest the cause(s) of default.

In much of existing ML-based research into default prediction, the challenge has been posed as a classification problem that categorizes a company's or sector's status as being in one of two states, namely, normal (= 0) and in default (= 1). ML modelling then involves calculating the probability that a company or sector can be classified as being in either a normal or defaulted state. Therefore, classification algorithms have mainly been used for default prediction, representative examples include SVMs, decision trees, and artificial neural network algorithms.

Model selection

However, the main problem with such a binary approach is that the data required to make classifications are complex, multivariate, with substantial breadth and depth. Multivariate time series forecasting focuses on predicting future values based on historical context. Using macroeconomic and financial conditions to forecast credit default swap (CDS) spreads is a challenging task. Mao et al (2023) propose the Merton-LSTM model, a modified LSTM model formed by integrating the Merton determinants model, to forecast the CDS indices. For the purposes of forecasting sectoral spreads and default probabilities we adapt the Mao et al (2023) approach underlying the Merton-LSTM model based on its ability to leverage the non-linear learning capability to learn the inherent association between the Merton determinants and sectoral CDS spreads. The superiority of the Merton-LSTM model in forecasting performance is attractive in long-term prediction even with a forecasting horizon extended to 28 days.

Data

Consistent with the Merton determinants model we use the following input data (Mao et al 2023 draw together a series of observations on the input variables, which we repeat below in the interest of clarity. For a complete view of the Merton determinants see Mao et al 2023 bibliography):

- Spot rate: a higher spot rate increases the risk-neutral drift of the entity's value process in the Merton structural model. A higher drift reduces the probability of default and lowers the credit spreads in turn. Duffee (1998) found a significant negative relationship between credit spreads and the spot rates.

- Term-structure slope: the level and slope of the term structure are the primary factors driving the spot rates which could further influence the CDS spreads. Slope steepening may increase default probability, thereby increasing the CDS index values.

- Volatility: the Merton structural model implies that the debt claim is similar to a short position in a put option. Given that option values increase with volatility, the Merton structural model therefore means that credit spreads will also increase with volatility, which in turn affects the default probability and therefore influences the CDS spreads.

- Equity's market value: the Merton structural model implies a negative connection between the reference entity's market value of equity and its probability of default. Further, the market value of equity is a reflection of market conditions which will also influence the recovery rate which is also likely to change over the business cycle.

6.7 Modelled Outputs: Volatilities & PDs

	Asset Class	Region	Risk Factor	Physical Risk - 1.5C				Physical Risk - 1C				Physical Risk - 0.5 C			
				1D	10D	3m	12m	1D	10D	3m	12m	1D	10D	3m	12m
Volatility	FX Vols (absolute % change in Normal vol)	Asia	USDINR 3M ATM Realised Vol	20%	20%	20%	20%	13%	12%	12%	12%	12%	10%	9%	11%
			USDJPY 3M ATM Realised Vol	10%	10%	10%	10%	8%	8%	7%	7%	6%	6%	6%	6%
		Europe	EURUSD 3M ATM Realised Vol	15%	15%	10%	10%	9%	8%	6%	8%	8%	7%	4%	7%
		UK	GBPUSD 3M ATM Realised Vol	15%	14%	11%	13%	10%	10%	8%	9%	7%	8%	6%	6%
		Other	USDBRL 3M ATM Realised Vol	20%	20%	20%	20%	13%	12%	11%	11%	10%	9%	9%	10%
	Equities Vol (absolute % change in Log-normal vol)	Asia	NIKKEI 3M ATMF Realised Vol	35%	35%	25%	20%	22%	24%	14%	12%	18%	19%	10%	9%
			NIKKEI 12M ATMF Realised Vol	35%	35%	25%	20%	23%	21%	16%	12%	16%	17%	13%	9%
		Europe	EUROSTOXX50 3M ATMF Realised Vol	30%	25%	20%	15%	16%	16%	14%	11%	15%	14%	11%	9%
			EUROSTOXX50 12M ATMF Realised Vol	30%	25%	20%	15%	19%	17%	13%	11%	13%	12%	9%	9%
		UK	FTSE100 3M ATMF Realised Vol	25%	25%	20%	20%	15%	14%	11%	11%	12%	13%	8%	8%
			FTSE100 12M ATMF Realised Vol	25%	25%	20%	20%	13%	12%	11%	12%	10%	9%	10%	10%
		US	S&P500 3M ATMF Realised Vol	30%	25%	20%	20%	18%	17%	11%	11%	15%	13%	9%	9%
			S&P500 12M ATMF Realised Vol	25%	25%	20%	15%	16%	17%	13%	10%	14%	12%	10%	8%
	Rates Vol (absolute % change in Normal vol)	Europe	EUR 1Y-1Y ATM Vols	15%	15%	10%	10%	8%	8%	8%	6%	7%	6%	5%	6%
			EUR 5Y-5Y ATM Vols	10%	10%	10%	10%	6%	6%	5%	5%	5%	5%	5%	4%
		UK	GBP 1Y-1Y ATM Vols	15%	15%	10%	10%	8%	9%	9%	6%	7%	6%	7%	6%
			GBP 5Y-5Y ATM Vols	10%	10%	10%	10%	7%	5%	5%	5%	5%	4%	4%	4%
		US	USD 1Y-1Y ATM Vols	15%	15%	10%	10%	8%	8%	7%	7%	7%	7%	6%	7%
			USD 5Y-5Y ATM Vols	10%	10%	10%	10%	7%	6%	6%	6%	5%	5%	5%	5%
		Other	BRL 1Y-1Y ATM Vols	20%	20%	20%	20%	12%	13%	11%	12%	12%	9%	9%	9%
			BRL 5Y-5Y ATM Vols	20%	20%	15%	15%	11%	11%	10%	8%	10%	9%	8%	7%
	Commodities (absolute % Price change)	Other	GOLD	10%	15%	20%	25%	8%	9%	13%	17%	4%	5%	6%	9%
			CBOT CORN	10%	15%	15%	20%	7%	7%	11%	10%	3%	4%	5%	5%
			COAL PRICE	15%	20%	20%	25%	8%	12%	14%	17%	5%	6%	8%	8%
			WTI CRUDE	15%	20%	20%	25%	8%	9%	13%	16%	4%	5%	7%	7%
PDs	Credit (absolute % change, in basis points)	UK/USD	USD 5Y CDS on UK 1 year implied PD	0.4%	0.3%	0.0%	0.0%	0.3%	0.3%	0.4%	0.8%	0.2%	0.3%	0.3%	0.6%
			USD 5Y CDS on UK 5 year implied PD	0.4%	0.4%	0.0%	0.0%	0.4%	0.3%	0.5%	1.4%	0.3%	0.3%	0.4%	1.0%

Table 12: Volatilities and probabilities for default (PDs) of the physical risk scenario with temperature sensitivities shown.

	Asset Class	Region	Risk Factor	Combined - 1.5 C				Combined - 1 C				Combined - 0.5 C			
				1D	10D	3m	12m	1D	10D	3m	12m	1D	10D	3m	12m
Volatility	FX Vols (absolute % change in Normal vol)	Asia	USDINR 3M ATM Realised Vol	25%	20%	15%	15%	15%	12%	11%	10%	14%	11%	9%	9%
			USDJPY 3M ATM Realised Vol	15%	15%	10%	10%	9%	8%	7%	6%	6%	6%	6%	6%
		Europe	EURUSD 3M ATM Realised Vol	20%	15%	10%	10%	12%	9%	8%	9%	11%	7%	6%	6%
		UK	GBPUSD 3M ATM Realised Vol	15%	15%	10%	10%	11%	9%	8%	9%	8%	8%	8%	6%
		Other	USDBRL 3M ATM Realised Vol	30%	20%	10%	20%	18%	11%	6%	12%	13%	9%	5%	8%
	Equities Vol (absolute % change in Log-normal vol)	Asia	NIKKEI 3M ATMF Realised Vol	40%	30%	22%	34%	27%	21%	15%	24%	20%	17%	11%	19%
			NIKKEI 12M ATMF Realised Vol	40%	30%	25%	22%	28%	21%	17%	14%	18%	15%	13%	11%
		Europe	EUROSTOXX50 3M ATMF Realised Vol	40%	25%	30%	30%	26%	15%	18%	18%	21%	14%	15%	15%
			EUROSTOXX50 12M ATMF Realised Vol	40%	30%	30%	20%	26%	18%	20%	14%	21%	16%	17%	10%
		UK	FTSE100 3M ATMF Realised Vol	30%	25%	20%	20%	20%	17%	11%	11%	16%	12%	8%	8%
			FTSE100 12M ATMF Realised Vol	30%	20%	10%	15%	22%	12%	7%	11%	16%	9%	6%	8%
		US	S&P500 3M ATMF Realised Vol	40%	25%	25%	20%	29%	16%	18%	14%	23%	13%	13%	11%
			S&P500 12M ATMF Realised Vol	25%	20%	20%	15%	17%	14%	13%	11%	13%	11%	9%	8%
	Rates Vol (absolute % change in Normal vol)	Europe	EUR 1Y-1Y ATM Vols	20%	10%	10%	10%	13%	7%	6%	6%	9%	5%	5%	6%
			EUR 5Y-5Y ATM Vols	20%	10%	10%	10%	10%	6%	5%	6%	9%	5%	4%	4%
		UK	GBP 1Y-1Y ATM Vols	20%	15%	10%	10%	14%	9%	7%	6%	11%	8%	6%	5%
			GBP 5Y-5Y ATM Vols	10%	10%	10%	5%	7%	6%	5%	4%	6%	4%	4%	4%
		US	USD 1Y-1Y ATM Vols	20%	10%	10%	10%	12%	7%	6%	7%	11%	6%	6%	5%
			USD 5Y-5Y ATM Vols	15%	10%	10%	5%	8%	5%	5%	3%	6%	5%	4%	2%
		Other	BRL 1Y-1Y ATM Vols	30%	20%	20%	20%	20%	13%	11%	12%	15%	9%	9%	10%
			BRL 5Y-5Y ATM Vols	20%	20%	10%	10%	13%	11%	8%	8%	9%	9%	7%	7%
	Commodities (absolute % Price change)	Other	GOLD	10%	15%	20%	30%	7%	10%	14%	20%	4%	5%	7%	9%
			CBOT CORN	10%	20%	25%	25%	8%	12%	14%	17%	4%	7%	9%	9%
			COAL PRICE	15%	20%	30%	30%	11%	15%	17%	23%	6%	8%	8%	11%
			WTI CRUDE	15%	15%	20%	30%	10%	12%	15%	19%	6%	6%	9%	10%
PDs	Credit (Absolute % change, in basis points)	UK/USD	USD 5Y CDS on UK 1 year implied PD	0.0%	0.0%	0.0%	0.0%	0.5%	0.3%	0.2%	0.3%	0.4%	0.2%	0.2%	0.3%
			USD 5Y CDS on UK 5 year implied PD	0.0%	0.0%	0.0%	0.0%	0.3%	0.3%	0.2%	0.2%	0.3%	0.3%	0.2%	0.2%

Table 13: Volatilities and probabilities of default (PDs) for the combined scenario with temperature sensitivities shown.

6.8 Impact Assessment Models

A summary of impact assessment models is presented in this section. The details of the mathematical formulas is covered in the second half of the section.

The value of the futures contract is calculated using the cost of carry model which is used to determine the theoretical price of a futures contract. It assumes that the futures price is equal to the spot price plus the cost of carrying the underlying asset to the delivery date of the futures contract. The formula considers the current stock price, risk-free rate, and time to expiration.

To assess the value of the option the Black-Scholes Model is used to calculate the theoretical price of call and put options. It assumes that the price of the underlying asset follows a geometric Brownian motion with constant volatility and that the risk-free interest rate is known and constant. The model considers the current stock price, option's strike price, time to expiration, volatility of the underlying asset, and risk-free interest rate to calculate the fair value of an option.

For pricing the forward contracts, the forward rate and forward points of a forward contract are calculated based on the spot rate, interest rates, and days to maturity. The forward rate is the exchange rate at which two parties agree to exchange currencies at a future date, while the forward points represent the difference between the spot rate and the forward rate. The forward points are calculated using the annual interest rates of both currencies and the number of days to maturity, and the forward rate is calculated by adding the forward points to the spot rate.

In the CDS pricing model, the survival probability is a crucial factor in determining cash flows and the value of the contract. The probability of default is the complement of the survival probability, and both probabilities add up to 1. The survival probability cannot be directly observed but can be implied from credit spreads on CDS contracts traded in the market. A bootstrapping algorithm is used to calculate the survival probability, which is then used in the pricing of CDS contracts. The recovery rate is set to 40

The equity valuation model involves several crucial calculations and functions to evaluate a company's financial health. These include calculating the compound annual growth rate, average margin, and forecast function to estimate future financial performance. It also involves obtaining the weighted average cost of capital and net debt to evaluate the company's financial health comprehensively. Finally, the EBIT figures are discounted to arrive at the present value of the firm's cash flows, providing a comprehensive overview of the company's financial position.

The Interest Rate Swap Valuation Model involves valuing a plain vanilla swap, which pays a fixed rate and receives a floating rate. The fixed and floating legs of the cash flows are calculated and discounted to the present value. The fixed leg is calculated by multiplying the fixed coupon by the number of coupon payments and discounting it to the present value. The floating leg is determined based on each six-month tenor on the forward curve, which is calculated for each point at which the swap is valued. Finally, the value of the instrument is obtained by subtracting the fixed leg from the floating leg.

The Bond Valuation Model uses the yield curve generated from the Hull-White one factor model to value government bonds at each simulated time step. The fixed coupon payments are discounted by their present value and summed, and the face value at maturity is also discounted and added to the sum of the coupon cash flows to determine the total value of the bond.

The Swaption Pricing Model uses the Black 76 model to determine the value of a swaption, which is an option on a swap. The function takes in several input parameters, including the start time of the swaption, forward rate, strike rate, risk-free rate, time to maturity, volatility, and number of cash flows. These parameters are used to calculate the value of the swaption using the Black 76 formula.

6.8.1 Future Pricing Model

The cost of carry model is a formula used to calculate the theoretical price of a futures contract. It assumes that the futures price is equal to the spot price plus the cost of carrying the underlying asset to the delivery date of the futures contract. The futures price is calculated using the cost of carry model where:

$$F = C * e^{(r_f - d)*T} \tag{47}$$

where F is the futures price, C is the current stock price, r_f is the risk free rate and T is the time to expiration

6.8.2 Black Scholes Option Pricing

The Black-Scholes Model is a mathematical model used to calculate the theoretical price of call and put options The model assumes that the price of the underlying asset follows a geometric Brownian motion with constant volatility, and that the risk-free interest rate is known and constant. Using these assumptions, the model calculates the fair value of an option by considering the current stock price, the option's strike price, the time to expiration, the volatility of the underlying asset, and the risk-free interest rate. The Black-Scholes Model is widely used in financial markets for pricing and risk management of options contracts. The formula for the price of a call option according to the Black-Scholes Model is:

$$C = S * N(d1) - X * e^{(-r*T)} * N(d2) \tag{48}$$

where: C is the price of the call option S is the current stock price X is the option's strike price r is the risk-free interest rate T is the time to expiration of the option (in years) N(d1) and N(d2) are the cumulative standard normal probability functions of the variables d1 and d2, respectively

The variables d1 and d2 are calculated as follows:

$$d1 = (\ln S/X + (r + (\sigma^2)/2) * T)/(\sigma * \sqrt{T}) \tag{49}$$

$$d2 = d1 - \sigma * \sqrt{T} \tag{50}$$

where σ is the volatility of the underlying asset.

6.8.3 Forward Contract Pricing Model

The forward rate and forward points based on the spot rate, interest rates, and days to maturity are calculated. The forward rate is the exchange rate at which two parties agree to exchange currencies at a future date, based on the current spot rate and the expected interest rate differential. The forward points represent the difference between the spot rate and the forward rate, expressed in pips or basis points. The spot rate of the underlying currency pair, the annual interest rates of both currencies and the number of days to maturity are required to calculate the forward points. The forward points are calculated using the formula:

$$ForwardPoints = (InterestRateEUR - InterestRateUSD) * DaystoMaturity/365 \tag{51}$$

Then, the forward rate is calculated using the formula:

$$ForwardRate = SpotRate + ForwardPoints \tag{52}$$

6.8.4 CDS Pricing Model

The survival probability is a crucial factor in determining cash flows and ultimately the value of a CDS contract. Understanding Credit Default Swap, cash flow structures depend on the occurrence or non-occurrence of a credit event. The likelihood of a credit event taking place is associated with the probability of default, which is the complement of the survival probability. This complementary relationship arises because the sum of the probability of survival and probability of default is equal to 1. Although the survival probability cannot be directly observed in the market, it can be implied from credit spreads on CDS contracts that are traded in the market. A bootstrapping algorithm can be utilized to calculate the survival probability from these credit spreads. These survival probabilities are then used in the pricing of CDS contracts.

6.8.5 Equity Valuation Model

To conduct a thorough financial analysis of a company, several crucial calculations and functions must be performed. The first step is to calculate the compound annual growth rate using past revenue data, which provides insight into the company's historical performance. Next, the average margin is calculated using past EBIT to determine the company's profitability. The forecast function is then run inside the simulation loop to estimate the company's future financial performance. In addition, obtaining the weighted average cost of capital (WACC) and net debt is essential to evaluate the company's financial health comprehensively. To calculate the net debt, the total debt is subtracted from the company's cash and cash equivalents. Finally, the EBIT figures are discounted to arrive at the present value (PV) of the firm's cash flows, providing a comprehensive overview of the company's financial position.

6.8.6 Interest Rate Swap Valuation Model

The interest rate swaps are valued for a plain vanilla swap, paying fixed rate and receiving floating rate. Each leg (fixed or floating) of the cashflows are calculated and discounted to the present value. Subtracting the fixed leg from the floating provides the value of the instrument. To calculate the value of the fixed leg, the fixed coupon (taken from market data at the reference date - 30th June 2023) is multiplied by the number of coupon payments (and discounted to the present value). The number of coupon payments assumes a semi-annual frequency and is therefore solely dependent on the duration of the swap. The floating leg is determined based on each six monthly tenor on the forward curve, which is calculated for each point at which the swap is valued.

6.8.7 Bond Valuation Model

The yield curve generate from the Hull-White one factor model is used to value government bonds at each simulated time step. The fixed coupon payments (taken from market data at the reference date - 30th June 2023) are discounted by their present value and summed. The face value at the given maturity is also discounted and added to the sum of the coupon cash flows to determine the total value of the bond at a given simulated time step. As the yield curve rises or falls at different tenors - in response to the climate shocks - the present value of the cash flows varies and produces a profit or loss with respect to the reference date.

6.8.8 Swaption Pricing Model

The Black 76 model is implemented to value a swaption, which is a simple swaption pricing model used to determine the value of a swaption (an option on a swap). To calculate the swaption value the function takes in several input parameters, including the start time of the swaption $t1$, forward rate F , strike rate X, risk-free rate r_f, time to maturity T, volatility vol, and number of cash flows num_{cfs}. The Black76 formula to calculate the call and put prices of the swaption is as follows:

$$d1 = [\ln(F/X) + (vol^2/2) * T]/(vol * \sqrt{T}) \tag{53}$$

$$d2 = d1 - vol * \sqrt{T} \tag{54}$$

where $nd1$ = cumulative distribution function (CDF) of the standard normal distribution for d1

and $nd2$ = CDF of the standard normal distribution for d2

$$df = e^{(-r*T)} \tag{55}$$

$$d3 = (1 - (1/(((1 + F/num_{cfs})^{t1*num_{cfs}})))))/F \tag{56}$$

$$call_{price} = df * ((F * nd1) - (X * nd2)) * d3 \tag{57}$$

$$put_{price} = df * ((X * norm.cdf(-d2)) - (F * norm.cdf(-d1))) * d3 \tag{58}$$

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