An Integrated Credit/Climate Scenario Approach Combining Firm-Level Climate Sensitivity with Climate Volatility Add-Ons

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All additional comments are welcome – any errors or omissions remain the responsibility of the authors. All our Credit Risk Modelling and Credit/Climate research papers and publications can be found on our website: www.z-riskengine.com.

Executive Summary

Introduction: Continued rises in global average temperatures together with the recent occurrence of extreme weather, fire, and drought events have heightened concerns over the possibility that climate change will have dire effects on future environmental and economic wellbeing. In response, financial regulators have formed the NGFS consortium, which creates scenarios to apply in climate risk stress testing ('CRST'). As now designed, the NGFS scenarios describe gradually evolving changes in economic and financial conditions under a variety of climate paths. But for depicting credit-risk stresses, one needs scenarios that depict sharp and unexpected deviations in cash flows, asset values, and volatilities from the trends produced by gradual changes. One commonly refers to such abrupt, deviation-from-trend events as 'shocks.' But how might one introduce such credit shocks into a climate-scenario model? We offer an answer to this question.

This paper presents a business-credit-risk model that, builds on our extensive empirical credit risk modelling research, by ***adding the systematic component of unexpected credit shocks to climate scenarios***. The model also allows for ***firm-level credit/climate trend effects on business PDs.*** One sees such firm-level effects depicted in recent studies including a couple from the ECB (2021, 2023). However, demand/supply analysis suggests that those trend effects could be both detrimental and beneficial and average close to zero. However, the relative impacts on high vs low-climate risk firms could be quite large. In contrast, the broader volatility rises postulated here due to long-run climate effects generally increases credit risk overall.

The main research question therefore focuses on ways to develop CRST scenarios that fully reflect the complexity of credit risk and which provide multiple channels for future climate change to influence credit risk portfolios.

Methods and Approach: In this paper we present an approach for developing CRST scenarios that combines firm-level climate physical- and transition-risk sensitivities with a multi credit factor model calibrated to market-based credit-cycle factors ('Z') derived from listed company PIT PDs (EDFs). In projecting the stochastic evolution of the credit-cycle factor for each selected industry or region, we apply our well-known Z second-order autoregressive (AR2) model calibrated to the historical time series of factor values. Focusing just on credit risk, the inclusion of the credit-cycle factors as inputs in the PD models for firms and the LGD and EAD models for facilities, produce the related PIT PD, LGD, EAD, and credit loss scenarios. PIT credit models provide key credit risk measures that along with TTC credit models as part of Dual Ratings systems that support multiple risk and regulatory objectives in banks. PIT credit measures are more accurate in that they reflect the systematic part of unexpected credit risk shocks that can be empirically measured – applying PIT credit measures is key for CRST scenarios.

To add prospective effects of climate change on credit-risk factors and thereby defaults and credit losses, we assume that the volatilities of the credit-factor innovations rise together with a specified climate-change metric (currently, global mean temperature: GMT). In our current approach, we start by projecting the rise in the volatility of innovations in the overall average credit-factor and then distribute that average result to industries, regions, (or firms) by applying beta coefficients based on emissions and location data. Since we have not yet acquired data on company-level emissions and locations, our illustrations to date use industry and region betas based on rough general estimates of the carbon intensities of industries. These preliminary illustrations do not include for now differences in firm-level climate exposures within sectors, in effect assuming that companies within each industry or region have the same exposures.

To model climate trend effects on an individual firm's TTC PDs, we assume that those PDs will trend up or down as indicated by a climate-change-sensitive model for each firm. Such models, in many cases, indicate that firms with high exposures to climate-change cost increases will have upward trending PDs and those with low exposures downward trending ones.

Further, note that we start with the same observed initial credit conditions in all climate scenarios. In effect, this means that we assume that the different scenarios involve only changes to future volatilities and possibly TTC PD trends and no change in current asset values and MtM leverage. In future work, we may relax this assumption and try to anticipate the changes in current asset values implied by a sudden change in market expectations regarding future climate-risk trends.

To date, our focus in developing the integrated CRST approach we present has been on specifying the modeling details – *by integrated we mean firm-level and dedicated industry sector and regional credit factors are combined in a single framework*. This paper following our other credit/climate papers completes the specification of the integrated approach. So far, we have also focused only limited effort on calibrating the effects of climate change either on trends or volatilities of credit-risk factors, therefore the scenario analysis presented here is to demonstrate how the approach works. As we pointed out in Aguais and Forest (2023, a) the correlation between rising GMT trends and the volatility of our credit factors is not yet statistically observable, suggesting formal model calibration will be an ongoing research effort. ***Thus, in the illustrative scenario and credit loss projections we present, we rely on assumed relationships, not empirically derived ones – however, the Z credit factors are fully derived empirically.***

Contributions: In Aguais and Forest (2023, b) we were the first to contribute an approach for applying rising credit factor volatilities related to climate change. For firm-level climate sensitivities, applying emissions and location data, one finds the primary approach outlined in recent ECB studies and other research. Building on NGFS scenarios, the proposed framework presented here is the first to combine foundational credit-factor models with firm-level credit/climate models to assess climate-change effects on credit risk through multiple channels. The integration of firm-level climate effects in the approach is also modelled as credit/climate trend effects through application of the concept of 'TTC Drift' which has also not been developed before in the literature.

By full credit risk models, we mean models that combine firm-specific credit risk effects with systematic credit factors representing unexpected shocks. The proposed integrated credit/climate approach builds on Aguais and Forest (2023, a, b, c, d, e and f) and the author's long-time credit modelling work (Forest and Aguais (2019, a, b and c), Chawla, Forest and Aguais (2015, 2016, a, b), and, Belkin, Suchower and Forest (1998, a, b) focused on building wholesale credit models for use in determining Basel capital, estimating ECLs for provisioning (IFRS9), and running stress tests.

Applying the Integrated Credit/Climate Scenario Framework: The integrated approach we present here is designed to directly incorporate the kinds of firm-level credit/climate models banks are currently working on, therefore, the approach is fully flexible. The Z-Risk Engine solution provides the credit factor models that could be combined with a bank's firm-level credit/climate models. We demonstrate a flexible scenario approach for developing two different CRST scenario *use cases*.

The first scenario *use case* develops stochastic scenarios over any time horizon by quarter for the credit factors and includes both firm-level credit/climate effects and rising climate-related volatility. The second scenario *use case* also includes firm-level credit/climate effects but applies deterministic credit/climate shocks as 'add factors' to Z industry sectors and regions to develop short-run climate scenarios as in Aguais and Forest (2023, e).

The key next tasks in our CRST modelling effort will focus on model calibration of the integrated approach we outline in the paper. We propose an approach for calibrating physical ('P') and transition ('T') climate factors to CreditEdge EDF credit measures.

To develop the various credit/climate scenarios presented here we use the Z-Risk Engine (ZRE) credit-factor solution, with the Z industry and region factors estimated from EDFs for 1990-2023 as second-order AR processes. To develop credit/climate scenarios to demonstrate the framework, absent a full model calibration, we use two key climate assumptions as follows:

(1) We apply the illustrative volatility multiplier approach using NGFS projections for each scenario's future GMT path, and,
(2) We apply a set of general industry and region sector beta assumptions that capture differential carbon intensity sector effects as proxies for a firm-level climate-sensitive PD model.

Using these key assumptions and the proposed approach we apply the framework to a roughly £140 billion UK/European credit portfolio to assess credit/climate scenario effects on various credit measures.

Contents

1.0. Integrated Climate Risk Stress Testing

1.1. Overview

In this section we summarize some key advances in the methods that analysts apply in developing scenarios depicting socio-economic, economic, and environmental trend impacts on financial risk measures in relation to climate change. This scenario analysis involves the complications of having to:

- consider the consequences of global warming trends that extend outside the range of documented experience,
- foresee, based on incomplete science, the effects of global warming on such things as extreme weather, melting of large ice masses, and ocean currents,
- anticipate the availability, effectiveness, and cost of future technologies for arresting climate change or adapting to it,
- consider future uncertainty in complex climate mitigation policy, and,
- link these broader 'climate drivers' to measures of credit risk.

Despite these complications, scenario analysis stands out as the most common technique used in evaluating effects of climate change. Thus, we review how CRST methods in the literature have been developed to support the management of climate-change impacts on financial risks and we highlight important concerns raised about the current methods. We then review ways in which CRST scenarios are applied in evaluating climate-change effects on wholesale credit portfolios.

We find that current CRST scenario approaches for credit risk do not apply fully specified, foundational credit models that would include both firm-specific and industry/region systematic unexpected 'shock' effects.

1.2. Climate Change

'Life on planet Earth is under siege …. [with] minimal progress made by humanity in combating climate change.' This statement appears at the beginning of '*2023 state of the climate report: Entering uncharted territory*.'[1] The report is one of many responding to the recently observed 'all-time climate related records and deeply concerning patterns of climate-related disasters.'[2] Continued increases in global CO_2 emissions and related rises in global mean temperatures ('GMT') suggest that environmental damage will continue to get more severe.

[1] See, Ripple, *et al.* (2023), page 1.
[2] Ibid., page 1.

Assessing the impact of climate change is an extremely complex task that many have suggested is dominated by 'radical uncertainty.'[3] Climate impacts have only been observed recently, but involve all interdependent aspects of the physical environment, global society, economic activity, and the financial system. The use of carbon-based energy is fully embedded E2E across nearly all social and economic activity implying a longer-run transition away from a carbon-based economy will require substantial *economic structural changes.*[4]

Climate research in recent years has developed a primarily top-down, deterministic scenario framework to characterize multiple future scenarios for Earth's physical climate, society, and global economic activity.[5] In the early application of climate scenarios, the focus has been to assess various climate policies and trade-offs including long-run physical climate risks by:

- creating several scenarios describing potential future paths for climate, socio-economic and economic variables, and,
- applying those scenarios in evaluating the economic damages from climate change and the costs and benefits of possible mitigation policies.

Integrated Assessment Models ('IAMs') stand central to much of this analysis. IAMs draw on several disciplines and often include models depicting the macro economy, energy production and use, CO2 and other green-house-gas emissions, regional climates, land use, demographics, and so on.[6]

'What-if' scenarios derived using IAM frameworks seek to anticipate a range of possible climate and economic futures as opposed to seeking to predict the most likely future outcome, and these scenario approaches often foresee a range of possible outcomes as opposed to just the most likely one.[7] Kemp *et al.* (2022) suggest that 'Prudent risk management requires consideration of bad-to-worst-case scenarios. Yet, for climate change, such potential futures are poorly understood. Could anthropogenic climate change result in worldwide societal collapse or even eventual human extinction?'[8]

In contrast to climate projections verging on catastrophic, for example see, Wallace-Wells (2019), more moderate scenarios assuming successful application of a variety of mitigation polices could potentially lead to less severe outcomes. Given the limitations in our understanding of the relationship between global warming and extreme weather and the shortcomings in our ability to foresee the effectiveness of actions taken to address the challenges posed by rising temperatures, climate scenarios need to span a wide range of possible futures. As Dembo and Latif suggest (2023), 'The uncertainty of climate change is

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[3] For a discussion of radical uncertainty and climate change see, Chenet, Ryan-Collins and Lerven (2021).
[4] For a discussion of climate and economic structural change see, Ciali and Savona (2019).
[5] Deterministic scenarios generally exclude complexity, see, Cliffe (2023), who highlights the broader complexity driving climate change, suggesting the world is characterized by, 'VUCA – Volatility Uncertainty Complexity Ambiguity'. On 'VUCA' and systematic climate risk impacts, see also, Kiesel and Stahl (2022).
[6] See Nordhaus (2013) and Asefi-Najafabady *et al.* (2021) for discussions related to IAM modeling.
[7] See, O'Neill *et al.* (2020) for a related discussion.
[8] See, Kemp *et al.* (2022), page 1.

such that no single scenario can adequately capture how a changing climate can shape the future'. [9]

In practical terms, uncertain climate change means that the future impact of climate stress could cover a very broad spectrum of consequences. Dembo characterises climate risk assessment as requiring a wide range of possible scenarios, referred to as a *'scenario spanning set.'*[10] Consistent with these concerns, a fair amount of criticism has been discussed in the literature, due to the fact, that current climate scenarios do not seem to include more extreme downside scenarios. Based on the deterministic, trend-oriented style scenario approach in IAM-based, NGFS scenarios, many question whether these scenarios represent a reasonable scenario '*risk spanning set*.' For climate scenarios, the fundamental questions that remain outstanding are, (1) do climate scenarios cover a reasonable 'spanning set' (range of scenarios), and (2) 'how bad is bad' which is an issue broadly of model calibration.

This paper focuses more narrowly on climate stress impacts on credit risk, therefore the answer to these key questions is part of what we seek to analyse with the proposed, integrated CRST approach. *By building climate scenarios on top of fully specified credit models that include past systematic shocks, the proposed approach is a big step in the right direction* for quantifying uncertain credit/climate effects in some degree of measurable terms, dependent upon model calibration.

1.3. Physical and Transition Climate Risks

The global effort to manage the impact of climate change on financial stability has focused on assessing two potential source of climate risks - *physical risk* could result from increasingly severe weather volatility, coupled with physical 'tipping points.' Observed GMT levels are rising and looking forward, Lenton *et al.* (2020), point out that "five major tipping points are already at risk of being crossed due to warming right now and three more are threatened in the 2030s as the world exceeds 1.5C global warming." [11]

To highlight one specific example of a potentially large, complex, interdependent climate shock, climate-driven population migration related to rising physical climate risks could have profound social and economic impacts. In 2022, by one estimate there were 36.2 million 'climate refugees', who were displaced by natural disasters due to climate change.[12] One estimate suggests that by 2070, up to '1- 3 billion people are projected to be left outside the climate conditions that have served humanity well over the past 6,000 years.' [13] *Assuming the average estimate of 2 billion, that would be a roughly 55-fold increase over 2022!* Rising physical climate shocks leading to, substantial population migration away from potentially uninhabitable parts of the Earth could lead to huge political, social, and economic upheaval, highlighting the extreme interdependence across climate complexity.

[9] See, Dembo, and Latif (2023), page 6.
[10] See, Dembo, (2019).
[11] See, University of Exeter (2023) and Lenton, *et al*, (2023).
[12] See, Apap and Harju (2023), page 1.
[13] See, Xu (2020).

Coupled with physical risks, climate related *transition risks* could result from abrupt carbon-related policy changes and complex, uneven structural change in economic activity and markets and it has been suggested these transition risks could lead to potentially disruptive carbon stranding shocks.[14] The Bank of England ('BoE') has suggested, 'Transition risks can occur when moving towards a less polluting, greener economy. Such transitions could mean that some sectors of the economy face big shifts in asset values or higher costs of doing business. 'It's not that policies stemming from deals like the Paris Climate Agreement are bad for our economy – in fact, the risk of delaying action altogether would be far worse. Rather, it is about the speed of transition to a greener economy – and how this affects certain sectors and financial stability.' [15]

1.4. Climate Risk Stress Testing

To assess climate change and financial stability in the banking system, CRST has become a key focus of financial regulators, policy makers and economists. Following Reinders (2023) we characterise CRST as focused on developing a framework for assessing the 'vulnerability of a portfolio, a financial institution or the entire financial system to adverse climate related hazards and scenarios to *physical* and *transition risk*.' [16] Developing a coherent CRST approach is a complex task and, as Cormack and Shrimali (2023) highlight; 'climate risk modelling in financial institutions is a relatively new, [novel] field, and it is evident that several challenges in the quantification of these risks need to be addressed – as a consequence, methodologies that are [currently] employed are in many cases incomplete and misleading'. [17]

CRST scenarios developed for the financial system apply deterministic 'trend-style, top-down' climate and economic projections from NGFS scenarios based primarily on IAMs. [18] The NGFS scenarios assess *physical risks* through projections of climate variables (GHG concentrations), GMT impacts and broad projections of weather patterns and rising sea levels. *Transition risks* are analysed by assessing the impacts of carbon mitigation policies (carbon taxes and green subsidies) on various financial measures. The general deterministic, 'what if' approach applied in CRST scenarios is not new, as it has its roots in traditional, short-run stress testing. Financial regulators currently require banks to apply a short-run,

[14] For a discussion of the Impact of potential carbon stranding shocks in the global oil and gas sector, see Semieniuk *et al.* (2022).
[15] See, Bank of England, (2019).
[16] See, Reinders *et al.* (2023) page 6.
[17] See Cormack and Shrimali (2023), page 1.
[18] See Allen *et al.* (2022, 2023), Vermeulen *et al.*, (2020), and Boirard *et al.* (2022) for key papers discussing the application of various top-down CRST scenarios.

'what-if scenario approach to derive conditional estimates [of extreme risk] under a given hypothesis.' [19] [20] [21]

In applying scenario analysis to climate change, Baer *et al.* (2023), provide a detailed review suggesting that 'all [climate] scenarios are wrong' but scenario analysis as a framework can be useful if the inherent limitations are clearly understood. A key contribution, of their paper and their ongoing research focuses on developing a broader taxonomy framework for how banks and financial regulators can develop and apply CRST scenarios to support a range business, financial, risk, and regulatory use cases. [22]

The distinction between current bank capital stress tests and evolving CRST scenario approaches is important for at least two reasons. First, short-run bank credit stress tests can be calibrated to past observed economic shocks that produce large cyclical increases in portfolio credit losses. CRST in contrast is quite different due to the lack of observed climate impacts on credit risk historically, suggesting CRST scenarios can't be calibrated to historical data. Compared to traditional bank stress testing, CRST also creates substantial modelling challenges due to global complexity. The 'overarching challenge of climate scenario analysis [is] to balance the 'applicability of scenarios with the required representation of complexities needed by the financial sector in the face of unprecedented risk, urgency of the transition and planetary boundaries.' [23]

Secondly, from an implementation point of view, regulators also seem to be moving toward some degree of integration of CRST with capital stress test policies and procedures required for banks. Based upon recent regulatory publications and industry discussions, it seems probable that the overall regulatory objective is to unify traditional stress testing and CRST from a policy and procedures point of view. If this is the overall objective, this also suggests assessing climate impacts using CRST scenarios could directly impact the regulatory capital banks are required to hold. [24] [25]

Given these key drivers complicating climate change scenario development, it is not surprising a substantial debate has developed within the industry and the CRST literature. Baer *et al.* point out, 'it is important to recognise that current IPCC and IAM-based scenarios were fundamentally not built for financial scenario analysis; they were built to inform policy.

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[19] See, Baer *et al.* (2023), page 2.
[20] In short-run bank capital stress tests, the application of 'what-if' scenarios are common. Regulators in most jurisdictions follow this general scenario approach by providing banks with short-run projections for key macro-economic and financial or market-based variables that banks then apply to their own credit portfolios to project 'stress credit losses'. The 'what if' approach for bank capital stress tests is well developed and riskier scenarios such as the US FRB CCAR 'severely adverse' stress scenario are benchmarked to past economic and financial shocks. The current 2023 CCAR 'severely adverse' stress scenario looks broadly like the 2007/08 'great recession'.
[21] A recent discussion of traditional stress tests vs CRST can be found in Cartellier (2022).
[22] Baer *et al.* have a forthcoming CGFI Discussion Paper that is tentatively titled, 'A scenario taxonomy for the financial sector.'
[23] See Baer, *et al.* (2023).
[24] The potential integration of climate scenarios with bank capital rules is a complex topic and part of an ongoing industry debate. For a perspective supporting integration of climate with bank capital rules see, Gelzinis (2021) and for the argument against, see, Anderson and Covas (2021).
[25] See Reinders, *et al.* (2023) page 6.

They were designed to explore the implications of different policy decisions, not to stress test.' [26] Climate impacts are not well understood in general and the highly complex dependencies with the real and financial sectors means that the impact of climate change 'is characterized by deep uncertainties and complex non-linear effects that materialise over an extended period of time.' [27] Baer *et al.* state that IPCC and IAM-based scenarios were created to inform policy and are not well designed for characterizing climate-related financial risk as noted above.

Cormack and Shrimali (2023) point out that there is a lack of transparency and consistency in the climate-stress test methods applied by banks. Cliffe (2023) opines that existing climate narratives and models downplay many key risks associated with climate change. T. Philipponnat (2023) suggests that current DSGM and IAM models produce excessively smooth and stable projections that ignore discontinuities that may happen under climate change. Reinders *et al.* (2023) and Bolton (2020) make similar remarks.

1.5. *CRST Scenarios Applied to Wholesale Bank Credit Risks*

To extend the NGFS scenario approach more directly to financial measures of credit risk, various country regulators have been leading this effort along with the ECB who has proposed a 'bottom-up' climate risk methodology linking top-down NGFS climate scenarios to firm-level financial risk impacts, see, ECB, (2021, 2023).[28] In Aguais and Forest (2023, g), we provided a review of the implied climate-sensitivity PD impacts from the two key 2021 and 2023 ECB CRST papers, showing they were substantially different.[29] Assessing firm-level credit risk impacts for climate change due to physical and transition risks in the ECB effort, 'trace climate-change's effects on companies to rising costs caused by greater physical damage, more stranded carbon assets and higher carbon taxes.' [30] The ECB approach of combining top-down NGFS scenarios with firm-level credit impacts through 'climate-sensitive credit models' is also evolving to a certain extent in Europe toward a de facto regulatory standard for CRST in banks.

[26] Baer, *et al.* (2023), page 2 – bolding added by the authors for emphasis.
[27] See Reinders, *et al.* (2023) page 6.
[28] For the ECB, see, Algoskoufis, *et al.* (2021), and Emambakhsh, *et al.*, (2023). We will generally refer to the Algoskoufis paper as 'ECB 2021' and Emambakhsh as 'ECB 2023'. Additional papers discussing climate change and credit risk can be found in Wambui (2023) and Novella (2022). Hangelbroek (2022) also presents an approach for undertaking climate-adjustments to European corporate PDs that is similar to the ECB approach. Baldassarri et al. (2020) also assess future firm-level climate related credit effects.
[29] In ECB (2021) the assessment of climate/credit effects assessed both physical and transition risks to 2050. In ECB (2023) the assessment looked at a time horizon to 2030 and included only transition risks. Applying only transition risk in the 2023 ECB paper over a shorter time horizon to 2030 would generally suggest smaller credit effects on wholesale PDs relative to 2021. The general explanation for higher not lower credit impacts *cet. par.* derives from the ECB applying conservative cost passthrough and green financing assumptions and also using a revised PD model calibration in the 2023 paper.
[30] See, Aguais and Forest (2023, b) page 2.

Current climate scenarios, as many have suggested, have a hard time representing the impact of climate uncertainty and complexity, in addition to also not capturing larger systematic credit cycles. This problem stems generally from the application of smooth changes in economic trends as, 'in these climate scenarios as currently applied, climate change slows economic growth, but does not affect cyclical variability in the factors influencing credit risk.'[31]

Absent climate effects, wholesale credit risk models are driven by two risk effects, firm-specific credit risk shocks (idiosyncratic) and occasional, large, unexpected systematic shocks impacting many firms simultaneously. These credit shock effects on observed credit losses have been well observed over the last roughly 40 years. Peak credit losses during the Great Recession reached about 3X long-run average credit losses on C&I loans as measured by the FRB C&I Loan Loss Index, as we see in **Figure 1**. Overall, we see that systematic shocks account for a substantial portion of observed wholesale credit losses.

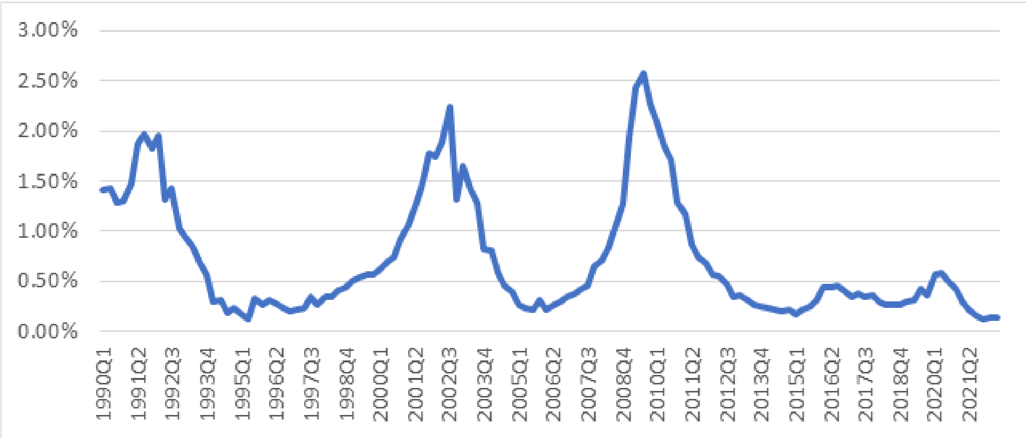

Figure 1: Annualized Charge-Off Rates of US Bank Commercial and Industrial Loans

Source: Federal Reserve Board

Credit models that consider only gradual changes in economic and financial variables perform comparatively poorly in explaining past credit losses. Large and abrupt, unexpected changes in economic and financial conditions account for much of past credit losses, especially those occurring during occasional periods of severe stress (**Figure 1). Figure 2** for 1990-2023 shows our Z-Risk Engine credit cycles for the Technology and Oil/Gas sectors, derived from our Z credit factor models estimated from Moody's CreditEdge EDFs.[32] We also see that the credit cycles in different industries and regions mostly move together, but at times can differ substantially (**Figure 2).** Our Z credit factors are defined as *first differences* and modelled as second-order AR processes – the application of factors as first-differences therefore focuses on '*shocks not trends.'* In **Figure 2**, at the industry sector level,

[31] Ibid., page 2.
[32] See, Moody's, (2016), and Nazeran and Dwyer, (2015),

similar, to aggregate credit losses, we also see large cyclical deviations in the factors from average credit conditions represented by the blue line at sigma = 0. The units in **Figure 2** are normalised standard deviation.

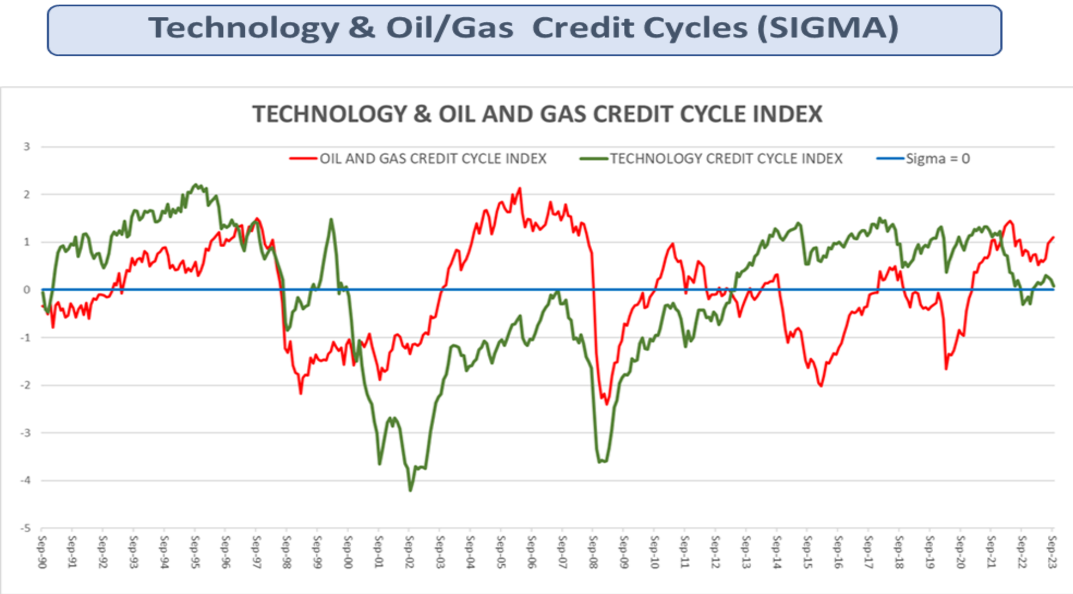

Figure 2: Credit Cycle Indices for the Technology and Oil/Gas Sectors

Source: Moody's CreditEdge EDFs and Z-Risk Engine Calculations (Sep 1990 to Sep 2023)

The historical credit loss cycles we observe in **Figure 1**, supports the development of well specified, empirical credit factor models that predict a component of unexpected credit risk shocks that we see in **Figure 2**. Our long-time work developing and implementing credit factor models can be found in Forest and Aguais, (2019, a, b, c) and, Chawla, Forest and Aguais (2015, 2016, a, b). These models have been approved to support multiple bank risk/regulatory use cases, including Basel II, stress testing and IFRS9.

Empirical studies drawing on default and loss data show that, to model business credit losses accurately on a point-in-time ('PIT') basis, the PD and LGD models must include inputs that track the occasionally large, unexpected variations in market values. For listed companies, these inputs could, as in the case of the Moody's CreditEdge model, derive from the market values, market volatilities, and book liabilities of the companies themselves. But in broader applications including unlisted companies, one must apply a related, but different approach. For this, one can create credit-factor indexes from the PIT PDs of listed companies (EDFs) grouped by industry or region. Then, for companies within each combined industry and region, include the relevant indexes as variables together with others measuring through-the-cycle (TTC) risk in the applicable PD and LGD models. Such models provide a solid basis for running credit scenarios. However, many current CRST studies as pointed out in Aguais and Forest (2023, b) fail to account for these unexpected shocks especially the broad cyclical ones underlying credit stress outcomes.

1.6. *A Framework for Integrated CRST for Wholesale Credit Risk*

The integrated approach we develop builds on our long-time credit factor modelling and our recent credit/climate research. The approach starts with current NGFS scenarios that are combined with the ECB firm-level approach that links deterministic physical and transition risks to firm-level PDs. The combined NGFS/ECB approach assesses credit/climate risk on wholesale company-specific PDs. Climate-change scenarios typically show upward trends in costs related to physical damage, transition to greener technologies, and selected policies (e.g., carbon taxes) designed to deter businesses from emitting CO_2 and other GHGs. The ECB approach assumes that some firms, particularly those with above average exposures to climate risk, only partly pass through these rising costs.

For such companies, incomplete cost passthrough causes profitability to trend down, book leverage to increase, and defaults and credit losses to drift up. Since these rises in default losses occur as trends, not as cyclical variations, we introduce them into our climate-scenario models by having the through-the-cycle ('TTC') PDs of credit portfolio exposures drift upward for 'brown' firms and potentially downward for 'greener' firms. The concept of TTC Drift as a way to apply the ECB approach in our proposed integrated solution was outlined in Aguais and Forest (2023, d and f).

We characterize these climate-driven, 'brown/green' firm-level PD changes as 'TTC Drift' because observed, long-run TTC PDs for given credit grades (bank internal or Rating Agencies) or for EDF-derived industries/region credit factors do not normally reflect rising or falling systematic trends. Therefore, systematic climate impacts on individual firms can be described as 'TTC Drift' relative to historically observed, stable TTC PDs (no drift).

It is important to note, that we discuss two distinct kinds of 'TTC Drift' in this paper. As described above, we integrate the ECB climate sensitive approach for assessing physical and transition risk by adjusting firm-specific PDs to reflect climate trend effects. In addition, we also develop the concept of 'Aggregate TTC Drift,' which is derived from aggregate climate effects that lead to rising, aggregate expected portfolio credit losses due to future rising climate on credit portfolio volatility.

This paper is organised as follows: in **Section 2** we discuss a high-level CRST model architecture to compare and contrast the current NGFS/ECB approach to the proposed integrated approach that expands the underlying credit model foundations. This simplified architecture is divided into a climate/macro model block and a climate/credit risk block. We also outline how the approach assesses combined credit/climate risk effects. Then we provide a brief review of key parts of the CRST literature to set the context for the proposed approach.

In **Section 3** we outline the key components of the proposed integrated approach and present the results of applying the integrated approach to a roughly £140 bil UK/European wholesale credit portfolio. We use the illustrative credit portfolio in conjunction with various NGFS scenarios to assess key CRST credit measures, including, PDs, expected credit losses (ECL) and credit risk 'tails' (UL). We also present an additional custom scenario suggesting a 3 Centigrade rise by 2050.

In this paper we derive the details of the proposed approach, but more formal calibration of the key climate parameters remains as ongoing research. Therefore, in applying the approach we make the following key simplifying parameter assumptions:

- The Z credit-factor volatility related to rising climate impacts, primarily physical risk, follows the illustrative approach presented in Aguais and Forest (2023, b), and,
- We apply a set of industry sector and region betas derived from various industry climate risk analysis as described first in Aguais and Forest (2023, c).[33]

Section 4 summarises the paper and provides a juxtaposition between the current, mainstream credit/climate CRST approach (NGFS/ECB) and the proposed integrated approach. In **Section 5, Appendix I** we provide the full, step-by-step derivation of the proposed CRST approach. In **Section 6, Appendix II**, we summarise the characteristics of the £140 billion credit portfolio we use to develop prospective credit/climate scenarios. In **Section 7, Appendix III** we outline an example of developing scenarios by applying the deterministic scenario use case that applies Z factor credit/climate shocks as add-factors. In **Section 8, Appendix IV** we present an example scenario for developing a dynamic net-zero portfolio strategy.

[33] We explain the industry/region credit/climate betas in more detail later, but these betas are aggregated for brevity and because we don't currently have a climate-sensitive PD model. The sector betas are proxies we apply for primarily cross-sector carbon intensity effects between high and low carbon sectors in the absence of applying a firm-level credit/climate model.

2.0. CRST Model Architecture and Brief Literature Review

2.1. Overview

To set the context for the integrated CRST approach presented in **Section 3**, in this section we:

- Compare a high-level CRST model architecture for the current NGFS/ECB approach to our proposed, integrated credit/climate framework,
- Review key aspects of credit modelling, and highlight the role of the Merton Model as the usual approach used to assess credit risk and systematic credit shocks,
- Highlight the key role that Point-in-Time credit measures and models play as the most accurate measure of credit risk,
- Review what we see as the two main strands of research driving current CRST scenario development, and,
- Summarize ways in which the two research strands in the literature relate to the proposed integrated approach.

We divide the CRST literature into two research strands; (1) recent studies that trace climate-change effects on credit risk to rising costs (*cost-passthrough*), and (2) studies that develop climate-change risk factors from financial-market data (*market-based*) and investigate the extent to which those factors affect the market values, values at risk, and PDs of financial and non-financial businesses. Given the density of CRST research, not all of the current research on climate scenarios fits exactly into the two strands we highlight, but we find this simplification helpful.

This brief literature review is not meant to be exhaustive, but it is focused on the most important research contributions we see as relevant for the CRST approach we propose. The following recent references provide a more detailed review of the CRST literature, including, Desnos *et al.* (2023), Reinders, Schoenmaker, and van Dijk, (2023), Baer *et al.* (2023), and Cartellier (2022).

2.2. High-Level CRST Scenario Modelling Architectures: Current (NGFS/ECB) vs An Integrated Credit/Climate Approach

We refer to the combined NGFS/ECB approach as the current, primary CRST approach which:

- Develops top-down, deterministic climate scenarios from a combination of NGFS scenarios, macro models, SSP and RCP pathways, and other satellite models,
- Assesses physical and transition climate risk sensitivity,
- Applies climate 'shocks' primarily as 'deterministic trend adjustments,'
- Analyzes carbon mitigation effects by applying various carbon tax/price assumptions,

- Specifies industry sector economic measures (GVA) usually as derived directly from 'down-scaling' of macroeconomic aggregates (not as dedicated sector models), and,
- Assesses firm-specific climate impacts by adapting mainstream wholesale credit models to add credit risk sensitivity to physical and transition climate risk factors.

Figure 3 shows a simplified model architecture for the NGFS/ECB scenario approach, where we summarize the current sub-components in the combined NGFS scenarios, within the top model block depicting 'climate/macro' risks. The lower model block depicts ways in which the top-down climate scenario variables influence climate-related credit risks. The main credit/climate channel is shown as impacting firm credit risk through transition and physical risk impacts on a firm's PD.

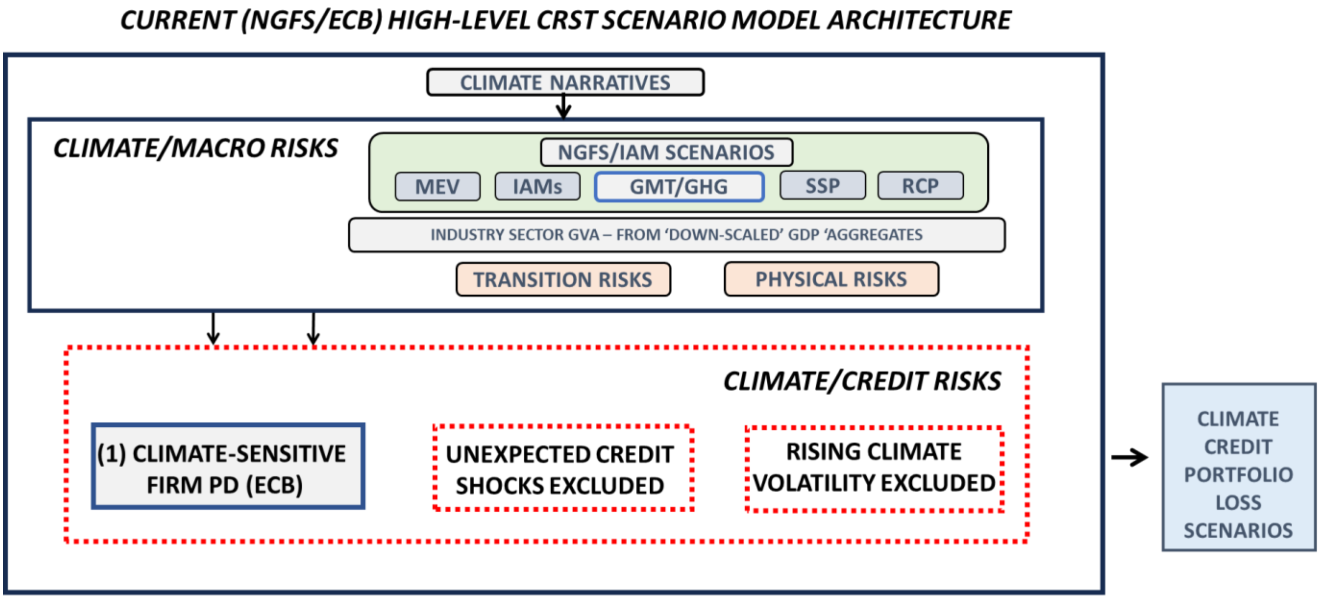

Figure 3: NGFS/ECB High-Level CRST Model Architecture

(The representation of Credit/Climate risks is shown as red dotted lines to suggest the current approach is only partially complete)

Figure 3 is a simplified representation but it captures the key model architecture and highlights the simplified, deterministic approach to assessing climate/credit risk. The NGFS/ECB approach, as currently specified, does not account for past, observed unanticipated credit risk shocks referred to as credit cycles. This approach also does not account for potentially rising future volatility that could increase the impacts of future climate or credit risk shocks. The integrated approach we present includes both of these key risk increasing effects.

In comparison, in **Figure 4** we show a high-level model architecture for our proposed integrated scenario approach.

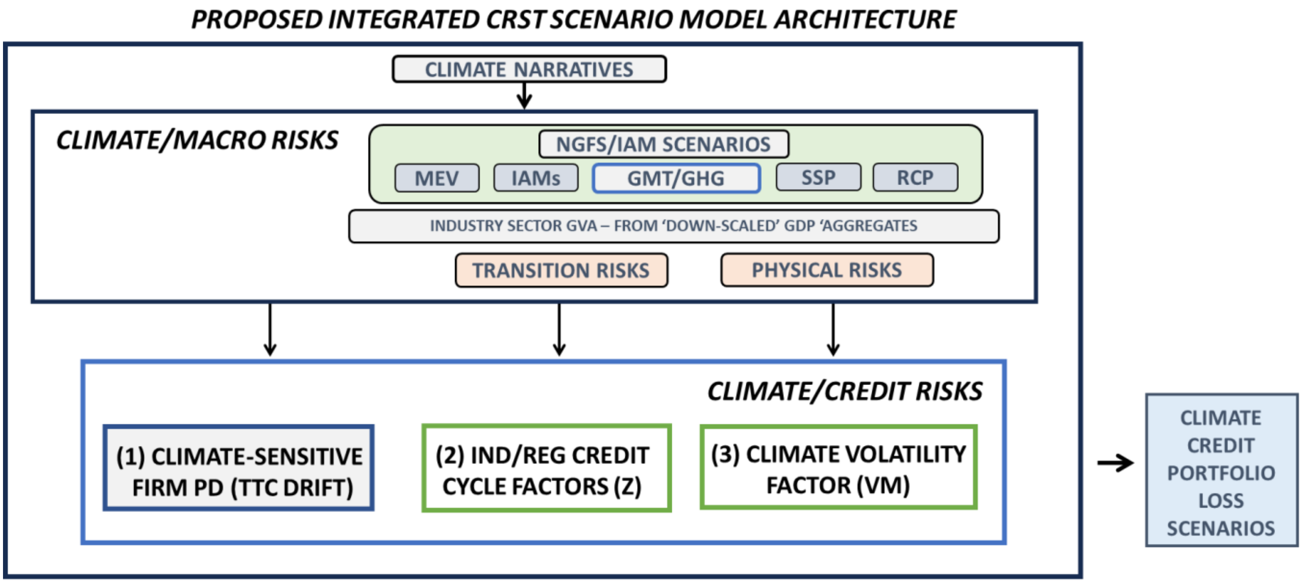

Figure 4: Integrated CRST Scenario Model Architecture

The proposed, integrated credit/climate scenario architecture shown in **Figure 4**:

- Applies the same top-down, deterministic climate scenarios and variables used in the current NGFS/ECB framework from the top model block,
- Also, applies the current ECB firm-level climate sensitivity approach as in **Figure 3**, as in box (1),
- Integrates past observed, unanticipated credit risk shocks through the Z sector/region credit factor model calibrated to past Moody's CreditEdge EDFs, as in box (2), and,
- Adds additional, future climate 'shock' impacts from rising GMT as rising volatility adjustments ('VM') to the future scenario paths for the industry and region credit factors as in (3).

In **Figure 5** below, we also show conceptually how wholesale PD models in the proposed integrated approach could incorporate the three key credit/climate risk scenario building blocks from **Figure 4**.

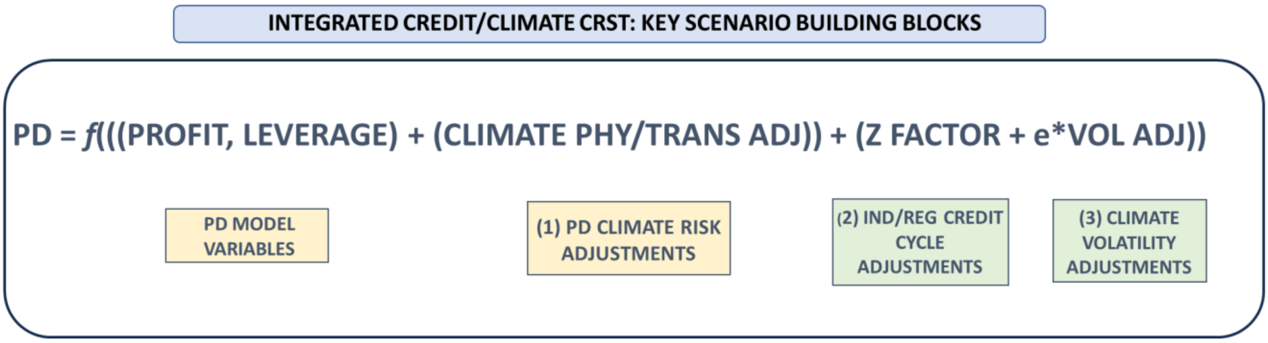

Figure 5: Integrated CRST: Combined Climate/Credit Impacts on Firm-Level PDs

The CRST combined credit/climate scenario four building blocks shown in **Figure 5** include:

(1) Bank's current firm-specific IRB PD Models (TTC)
(2) Physical and transition risk sensitivity added to firm-specific PDs:

- Follows the general ECB approach or alternatives
- Implemented as 'TTC Drift' climate sensitivity trend adjustments

(3) Systematic credit risk shocks added through sector/region Z credit cycle factors
(4) Rising climate induced volatility by linking climate variables like rising GMT to rising adjustments to the Z innovations ('e') in the credit factor simulations as in Aguais and Forest (2023, b)

In **Figure 5**, the PD-boxes shown on the left in **Figures 3 and 4**, have been split into separate PD model components for the usual PD specification (TTC) and the separated climate sensitive adjustment. Overall, the integrated approach shown conceptually in **Figure 5** supports two scenario development use cases, based on either stochastic or deterministic credit/climate shocks.

2.3. Modelling Credit/Climate Risks

2.3.1. Credit Modeling Facts and the Merton Model

Most credit models depict default risk as arising from unexpected shocks, not foreseeable trends. We see this in the following description of the Merton model of business default risk. Today one can observe a firm's past and present asset value in relation to liabilities and cash flow relative to debt service. If a firm currently has appreciable margins of asset value over liabilities and cash flow over debt service, it is solvent. In explaining the probability of such a firm defaulting over a chosen horizon such as the next quarter, year, or three years, the Merton model addresses the following question: how likely is it, at any time up to the horizon, that a series of shocks to asset value over liabilities or cash flow over debt service would cause the firm to default?

To get quantitative answers to this question, one specifies and estimates a model for the stochastic evolution of a firm's assets/liabilities or cash flow/debt service relative to identified default barriers. Shocks can either be idiosyncratic, specific to a firm, or systematic, shared by many firms. In the data on past defaults and losses, one sees evidence of occasionally large, systematic shocks as in **Figure 1**.

The so-called Merton model provides the central approach to modeling default risk of firms. Under Merton, default arises from the interplay of leverage and volatility, with leverage typically defined as the logarithm of the market value of assets over the book value of liabilities and volatility as the standard deviation of future probabilistic leverage.[34] High leverage implies a small margin between assets and liabilities and thus a comparatively high probability that asset value in the future will fall below liabilities by enough to trigger default. High volatility implies a wide range of future leverage values, with a comparatively high probability that assets will fall relative to liabilities by enough to cause leverage to drop below a solvency threshold value. High leverage and high volatility together imply an even higher probability of default. Low leverage and volatility imply the reverse.

In almost all formulations, the Merton probability of default model is convex in the range of PD values encountered in practice. This convexity implies that a symmetric distribution of future leverage values produces an asymmetric distribution of PD values, with comparatively high PDs occurring more frequently than in a normal distribution. This explains how one gets realistic asymmetric credit-loss distributions from symmetric leverage shocks. See Belkin *et al.* (1992) and Chawla, Forest and, Aguais (2016, a) for a discussion of this convexity property. Further asymmetry may arise if the leverage shocks themselves are asymmetric.

The Merton-style PD model applies to the full range of wholesale credit applications, including those focusing on climate-change effects.[35] To get the PD impacts of climate change on business PDs, one must estimate the transition- and physical-risk effects on cash flows, asset values, leverage, and leverage volatilities of firms. One then enters those inputs incorporating those effects into a Merton model. *Under varying climate scenarios, the inputs change, not the model.* Consistent with the literature, we focus primarily on PD but the same remarks apply to LGD and EAD modelling.

2.3.2. Market-Value Credit Inputs Required for Assessing PIT Credit Measures

Many credit rating models within banks and credit-grading agencies (e.g., S&P, Moody's, Fitch) involve only book value financial ratios and credit-analyst judgmental assessments for the inputs determining PDs or rating grades. However, the PDs arising from such models explain little of the wide cyclical variations in default rates and thus are considered as

[34] See, Kealhofer, (2003), and Capasso *et al.* (2020) also utilize a default-distance approach as a starting point in assessing credit/climate impacts.

[35] For clarity we use the term 'wholesale credit' to apply to large corporate and SME, commercial borrowers, and exposures.

producing close to through-the-cycle (TTC) measures. As first revealed by KMV in the late 1980s, to produce point-in-time (PIT) PDs that track at all closely the cyclical variations in default rates, a default model must include market-value inputs.[36] Dual credit rating approaches include both TTC and PIT credit measures to support multiple bank risk and regulatory objectives, with our extensive credit model research over the last 20 years having led the way in designing and estimating PIT/TTC dual ratings. See, Aguais, et al. (2004, 2007) for early methodological foundations of PIT/TTC credit models.

Point-in-Time (PIT) Versus Through-the-Cycle (TTC) Credit Models: Point-in-time (PIT) credit models attempt to explain the default and credit-loss rates of firms, credit facilities, and credit portfolios at each time point. Through-the-cycle (TTC) measures explain only relative default and credit-loss rates of individual firms and facilities at each time point, with the numerical rates for broad portfolios set to long-run average values. Since default and loss rates vary over time, with the highest default rates of broad portfolios over a year standing above long-run average values by more than 2.5X and with the highest annual loss rates rising above long-run average values by more than 3X, successful PIT models have been shown empirically to estimate default and loss rates much more accurately than TTC ones due to systematic credit cycles. In past trials with estimating default models, we have obtained a goodness of fit at least double that of a close-to-TTC model by adding Z indices designed to translate the model into a PIT one.

Credit Cycle DDGAP and Z Credit Factor Indices: As explained in the text, ZRE's credit-cycle DDGAP and Z indices arise by summarizing, for selected segments such as industries or regional groupings, the listed-company PDs from a PIT model such as Moody's CreditEdge. By adding these indices as inputs to an otherwise close-to-TTC model such as those commonly used by banks in determining credit grades, one gets PIT measures which are now required for projecting expected credit losses used in for determining loss provisions under the IFRS9 or CECL accounting standards for bank provisions.

See below (Figure 6), from one of our earlier research papers, Forest and Aguais (2019, c), the PIT estimates obtained by adding Z indices to a TTC model explain the time series of US C&I loan-loss rates much more accurately than the flat TTC values. For the Federal Reserve loan loss charge-off data, Z-factor adjusted PIT model estimates of loan charge-offs are substantially more accurate in predicting observed historical loan losses as compared to flat, long-run TTC loss estimates.

36 See, Kealhofer, (2003) and Moody's, (2016). 'KMV' was a firm founded by, S. Kealhofer, M. McQuown, and O. Vasicek that pioneered the EDF methodology and was acquired in 2002 by Moody's Corporation.

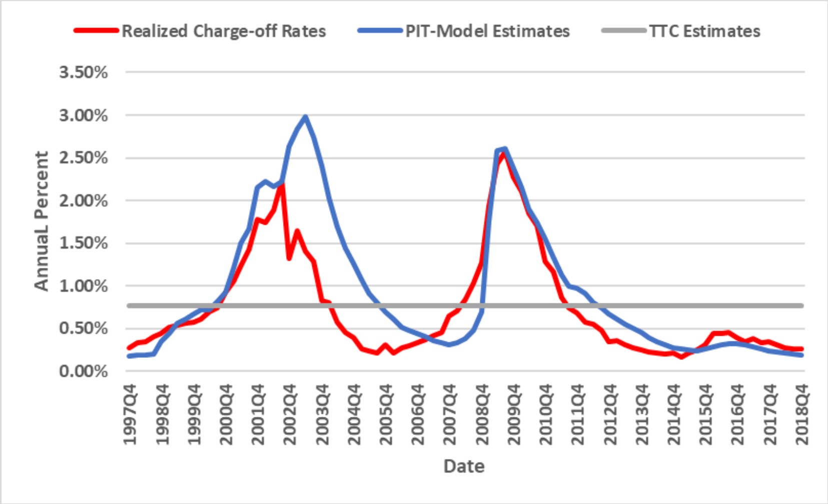

Figure 6: PIT and TTC Loss-Rate Estimates Compared with Realized Value

Source, Forest and Aguais (2019, c)

As another example, we see in **Figure 7** the importance of applying market-based measures to assess PIT risks. **Figure 7** provides a comparison of default rates estimated alternatively by the Moody's RiskCalc Financial-Ratio-Only (FSO) and Credit-Cycle-Adjusted (CCA) models. The CCA model adjusts the FSO estimates for the credit-cycle effects implied by market-value measures. Ignoring level differences reflecting RiskCalc adjustments for entities that stop reporting, we see that only the CCA model tracks the cyclical variations at all closely. We use the Moody's RiskCalc model example to show the increased default rate accuracy because the RiskCalc CCA model applies a similar credit factor approach as our Zs.

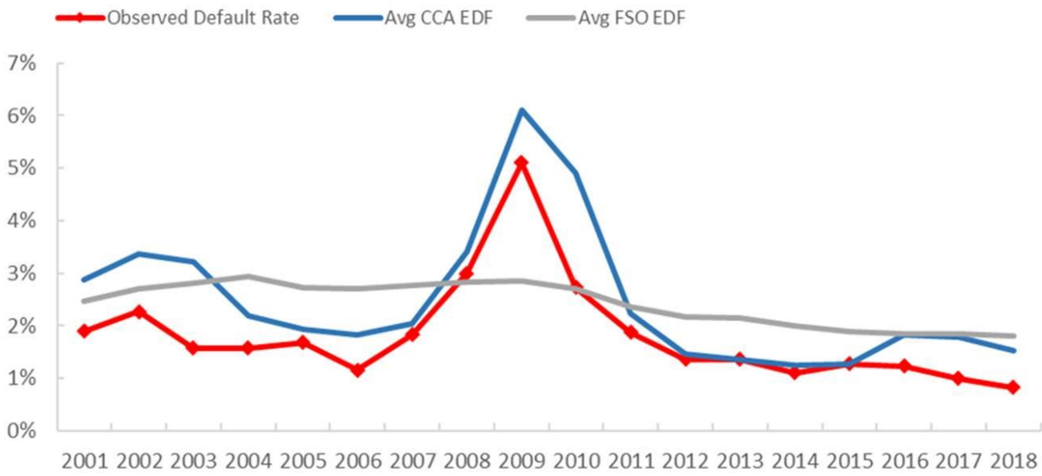

Figure 7: RiskCalc EDF Credit Measures vs Observed Default Rate

Source: Buitrago et al. (2019).

2.4. Climate-Change Credit-Impact Studies

Many recent studies on the effects of climate change on credit risk fall within one of two strands of research. In one strand, climate-change-related cost increases reduce the profitability of some firms and thereby raise their probabilities of default (PDs). In the other research strand, shocks in financial-market-derived climate-risk factors reduce the market values of some firms and thereby raise their PDs.

2.4.1. Cost-Passthrough Studies

In several recent studies, incomplete passthrough of climate-change-related cost increases cause profitability to fall and defaults to rise. Those cost increases could derive from such things as higher carbon taxes, faster asset obsolescence, brown-to-green-transition missteps, or rising physical damage caused by wildfires, droughts, floods, cyclonic storms, and so on.

Incomplete cost passthrough along with increasing leverage accounts for the climate-change impacts in the two ECB studies (2021, 2023). In both cases, the studies assume that firms:

- pass through only part of the cost increases related to climate change,
- make no effort to mitigate the related effects on credit risk through deleveraging, and,
- finance green investments entirely with debt, thereby causing leverage to rise.

Instead, at least for carbon taxes, as implied by long-run demand/supply analysis, one might assume that the cost passthroughs would be incomplete, complete, or more than complete depending on whether a firm experienced above-average, average, or below-average cost rises. Indeed, the broad economy-wide recycling of carbon-tax proceeds could, under some policies, lead to small increases in GDP and employment and smaller declines in overall PDs on an aggregate basis. Further, one might assume that firms would finance their green investments with the customary mix of debt and equity and one might assume that firms at least partly offset the unrecovered cost rises by deleveraging. Under these alternative assumptions, the estimates of overall climate-change impacts would be smaller.

Reinders, Schoenmaker, and van Dyke (2022), apply discounted-cash-flow analysis linked to a Merton contingent claims model in estimating effects of a carbon tax on equity and debt valuations under the alternative assumptions of 0% and 50% passthrough. While the authors refer to the carbon tax as a shock and distinguish it from ongoing policies already priced into business asset values, the results reflect somewhat less than plausible assumptions on the nature of policy changes. As a general rule, illustrated by the US Federal Reserve's practice of forward guidance, major policy changes almost never occur as abrupt shocks. Instead, they get phased-in gradually, following an extensive review process. However, while the policies themselves might be phased in, one might still find that market anticipations related to the possibility of carbon taxes or other climate-related phenomena could change abruptly, affecting business PDs. As an important insight on beneficial effects of cooperation, less-than-full passthrough leading to credit impacts could also occur if neighboring countries fail to match the tax.

Desnos, *et al.* (2023) examine the effects of carbon taxes on costs in an industrial input-output framework extended to include greenhouse gas emissions. The study derives a range of impacts under varying assumptions on cost-passthrough rates related to demand and supply elasticities. The study presents results from running Monte Carlo simulations in which passthrough rates and passthrough correlation coefficients are stochastic.

The carbon tax studies involve standard demand/supply analysis of the effects of an excise tax. Most of these studies try to estimate the effects on profit margins and thereby, apply further assumptions, on PDs. The impact on margins and credit risk depends on the shape of both the demand and supply curves as we show examples in **Figure 8**. Under perfect competition, the long-run supply curve is horizontal and effects on margins and credit risk would be small. With upward sloping supply due to firms differing in their scarce-resource endowments and with some firms earning rents, cost passthrough could be incomplete, margins compressed, and PDs raised.

As a separate point, even in this case of upward sloping supply, the effects on outputs, prices, and margins depend more broadly on how the tax revenues are recycled. While the excise tax shifts supply down, recycling of tax proceeds shifts demand up. **In Figure 8**, as shown in the middle panel, for firms with average carbon intensities, one would expect prices to rise roughly in line with the tax (mostly full cost passthrough), implying limited changes in margins, default risk, and outputs.[37] Observe that the margins on sales correspond to the gaps between the horizontal price line and the supply curve. The left-hand panel for high carbon intensity firms shows margins compressed and the right-hand panel for low carbon intensity firms shows margins expanding.

Outputs overall as indicated by the middle panel for average intensity firms remain mostly unaffected, which is as intended since the excise tax is not designed to be an austerity (or stimulus) measure. Thus, macroeconomic analyses of carbon taxes, see Pomerleau and Asen (2019), typically find relatively small economic effects and, under some recycling schemes, potentially positive impacts on output and employment.

[37] See, European Commission, Directorate-General for Climate Action (2015) for empirical estimates of cost-passthrough measurements by industry sector.

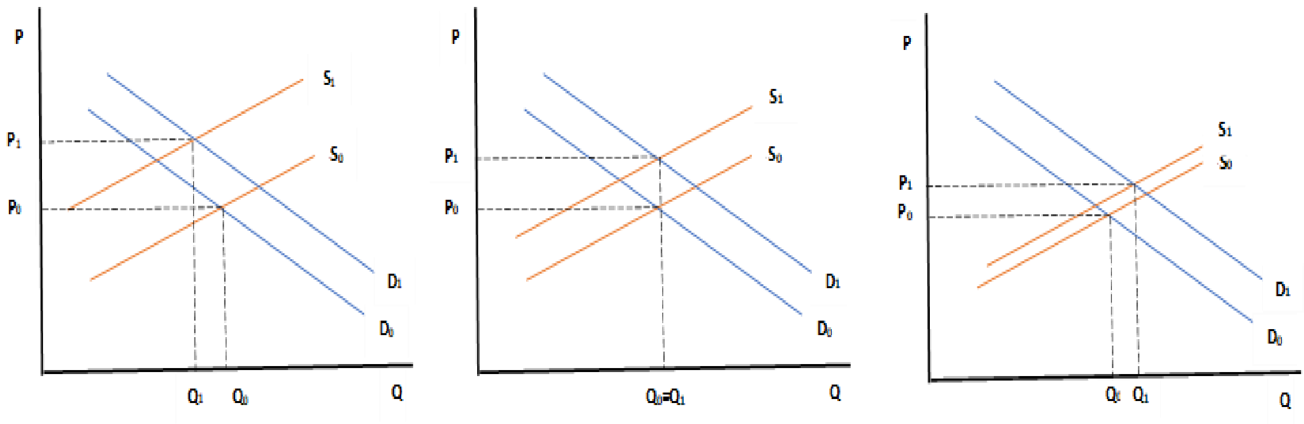

Figure 8: Carbon-Tax Supply and Demand Shifts for Products with Above Average (Left Panel), Average (Middle Panel) and Below Average (Right Panel) Carbon Intensity

Thus, one would expect carbon taxes to have limited overall effect on PDs, but with highly carbon intensive firms suffering rises and low carbon intensive firms experiencing declines. However, even this limited result requires the further assumption that firms fail to adjust leverage in responding to changes in sales margin. Such changes in leverage represent a possible behavioral response. At present, we know of little empirical evidence on its magnitude.

Rising incidence of physical-risk events shifts supply down (through such things as more business interruptions and faster capital depreciation). Here, no revenue recycling occurs. With more output diverted to capital replacement, consumption growth will slow and with productivity impaired by business interruptions, output growth may slow as well. The effects on margins and credit risk would likely be small in the aggregate, with adverse (beneficial) effects on high-risk (low risk) firms. Again, deleveraging could somewhat mitigate the impacts.

2.4.2. Financial Risk-Factor Approaches

This second strand of research draws on market-price data in attempting to identify climate-risk impacts.[38] This typically involves building climate-risk factors based on structured portfolios of equity prices and then investigating the statistical relationships between these factors and other market prices or credit-worthiness measures. One approach creates a so-called brown-green transition-risk factor as a long-short equity portfolio, with long positions in high-emission companies and short ones in low-emission companies. Most of the studies find statistically significant and often increasingly strong relationships between market prices (e.g., of financial institutions) and transition-risk factors, but typically statistically insignificant relationships for physical-risk indicators. The absence of a statistical relationship between market values and physical risk is disappointing since physical risk represents the fundamental threat from climate change and transition risk is a derivative of that.

[38] Bansal, *et al.* (2019) as one example, provide analysis of correlations between climate and market prices, 'We also find that long-run temperature fluctuations carry a significantly positive risk premium in equity markets.', see page 30.

Jourde and Moreau (2023) build transition and physical risk factors based on long-short portfolios of equity issues and find that financial-institution returns respond significantly to the transition-risk factor but only insignificantly to the physical risk one. Jung, Engle, and Berner (2023) construct a variety of financial-market-based transition-risk factors and find that bank returns react negatively to shocks in each of the transition factors, with the relationships statistically significant in three out of four cases. Novella (2022) finds a negative relationship between Eurostock company default distances and carbon intensities. Farallia and Ruggiero (2023) find a positive correlation between CreditEdge EDFs and transition-risk indicators and identify the volatility component of EDFs as the main channel of influence.

2.5. Summarizing Climate Impacts in the Integrated Approach

The integrated model we propose combines two sources of climate-change-related credit risk, one characterized by upward or downward drift in individual firm TTC PDs based on direct climate effects and the other by rising cyclical volatility in the industry and region credit-risk factors influencing PIT PDs, LGDs, and EADs. In general, in the credit/climate literature, the focus is usually on assessing PD effects only. The Z-Risk Engine solution assesses key credit models for PD, LGD and EAD on both a PIT and TTC basis, so the approach is more general than much of the climate risk literature, but the application of TTC Drift presented here is just on PDs.

The cost passthrough approach is applied in the firm-level ECB climate scenario approach as TTC Drift and the Zs we apply are market-based, so they are consistent with the market-based literature. At the end of **Section 5, Appendix I**, in **5.6,** we suggest ways to derive physical and transition factors mentioned above and link them to our Z credit factors to refine the climate factor calibration and application that would be an extension to the concept of the climate volatility multipliers.

3.0. Applying the Integrated Approach to Assess Climate Risks

The climate-sensitive ZRE model extends our existing approach to projecting PIT PDs, LGDs, and EADs by including two sources of climate-change-related credit risk. The first one is characterized by upward or downward drift in individual firm TTC PDs, with this caused potentially by differences in climate-cost-passthrough rates. The second effect occurs due to rising cyclical volatility in the industry and region credit-risk factors influencing PIT PDs, LGDs, and EADs. Most of the existing credit/climate literature considers PD effects only.[39] Therefore, the interaction of firm-level climate sensitivity effects with fully specified credit risk factor models subject to climate volatility effects represents a new contribution to the credit/climate literature.

3.1 Climate Sensitivity Modelled as Firm-Specific TTC Drift

Here we assume that businesses face gradually increasing costs tied either to policy-driven, potentially costly transitions from higher- to lower-emissions technologies or to rising physical damage caused by climate change. In markets with upward-sloping, long-run supply curves, the cost increases of firms with above average climate exposures may be less than fully passed through into prices, thereby causing profit margins to decline. On the other hand, the lesser cost increases of firms with below average exposures may be more than fully passed through (with market price rises set by the cost increase of the average-exposure firms), causing margins to increase. Under the further assumption that firms with falling profitability choose not to fully offset this through deleveraging, debt coverage would trend down, causing PDs to drift up. Under similar assumptions, the firms with below average exposures would have PDs drifting down. The net aggregate effect in each case would likely be small, which is broadly consistent with most credit impact studies published so far.

As we outlined in Aguais and Forest, (2023, d, f) it is possible to apply the climate sensitivity impacts on firm-specific PDs derived from an ECB-style PD model as TTC Drift. In our first TTC Drift research note (2023, d) we demonstrated the concept of TTC Drift as a shift over time for an aggregate credit portfolio by shifting downward the aggregate credit grade distribution. In (2023, f) we refined this suggestion and proposed using an ECB-style climate sensitive PD model to derive a time-series of firm-specific, annual PDs over the scenario horizon. These climate-sensitive PDs would reflect for each firm the physical and transition risk impacts of various NGFS scenarios. Climate-adjustments would be applied to an ECB-style PD model that estimates the future cost rises and profits squeezes tied to climate-change mitigation policies and to increasingly severe physical impacts of climate change. We include those effects by having the TTC PDs for individual firms in a credit portfolio being

[39] The 2021 ECB approach did include indirect climate impacts on LGDs through collateral re-valuation but most emphasis in the related literature focuses on PD climate sensitivity primarily.

modeled as a drift upward or downward at the rates indicated perhaps by an ECB-type PD model.

3.2 Rising Climate Risks Applied Generally as Increases in Risk-Factor-Volatilities

In this case, we assume that the volatility of credit-risk factors (Zs) rise as climate-change occurs, and we have developed a general volatility multiplier but in principle separate volatility multipliers could be applied for each industry sector and region Z. The Z factors track the unexpected changes in the systematic credit conditions that cause PIT PDs, LGDs, and EADs to rise and fall broadly. The climate-related increase in Z vols leads to higher values for both expected and especially stress (high percentile) losses. *Therefore, future simulated climate shocks produce larger effects relative to historical credit shocks on their own due to climate impacts.* These rising combined credit/climate shock impacts will be much larger in high emission, high carbon intensity sectors. The expected credit risk increases tied to rising vols are separate from those caused by climate-related cost rises (TTC Drift). As in **Figure 4**, the approach assesses two different channels for climate to impact credit risks.

We include these effects by having the volatility of Z innovations rise over time at rates implied by a climate-change metric. As in Aguais and Forest (2023, b), we specified the vols to rise on average at rates implied by the GMT increases in a chosen NGFS climate scenario. In ongoing, future climate research, for calibration and implementation of the integrated approach, we plan to assess having the Z vols change potentially at the rates implied by market-derived transition-risk (T) and physical-risk (P) factors. Current industry, exploratory studies for example, are extracting such T and P factors from structured portfolios of market prices. In future model calibration, after obtaining an overall rise in vols, we could distribute that average rate of increase to various segments or even firms by applying 'beta' coefficients reflecting relative transition- and physical-risk exposures. Thus, industries with greater than average (lower than average) exposures experience above-average (below-average) vol rises.

We next apply the Z models with rising vols in running Monte Carlos sims of credit losses. Climate scenarios with higher vol rises will have greater credit losses. Alternatively, ZRE can run deterministic scenarios in which the inputs of Z-innovation paths ('add factors') derive from detailed climate narratives for a particular climate scenario as we outline in **Section 7, Appendix III** based on Aguais and Forest (2023, e).

3.3 Integrated Model Approach Description

The integrated model includes both the TTC drifts and the vol rises implied by a climate scenario. The estimated losses will then combine the effects of both sources of climate-related credit risk.

Here we briefly describe the extended ZRE model applied in running CRST scenarios that combines firm-level climate physical- and transition-risk sensitivities with a multi credit factor model calibrated to market-based default-risk measures. For a detailed mathematical description of the modeling approach see **Section 5, Appendix I**.

We start with the existing ZRE application that involves DDGAP ('Default Distance GAP') and Z credit-risk-factor indices for each of several industries and regions. ZRE obtains those indices by:

- converting the point-in-time (PIT) PDs of listed firms from a model such as Moody's CreditEdge into default-distance (DD) measures,
- summarizing those DDs of listed firms within an industry or region by computing medians,
- forming DDGAPs by normalizing the median DDs around the long-run average of those median DDs, and
- creating Zs by dividing the DDGAPs by the standard deviation of annual DDGAP changes.

Next, we project the stochastic evolution of the Zs (and DDGAPs) for each industry or region. ZRE accomplishes this using autoregressive second order (AR2) models calibrated to the historical time series of Z values.[40] After that, by entering the credit-cycle-indices for stochastic or deterministic scenarios into the PD models for firms and the LGD and EAD models for facilities, ZRE produce the related PD, LGD, EAD, and credit loss scenarios.

To allow in ZRE for prospective effects of climate change on credit-risk factors and thereby defaults and losses, we assume that the volatilities of the Z-factor innovations rise together with a specified climate-change metric (currently the global mean temperature: GMT). To model trend effects associated with such things as cost passthrough, we assume that the TTC PDs of individual firms will trend up or down as determined by a climate-sensitive PD model for that firm. Presently, in modeling the climate-change volatility increases, we start with a relationship determining the overall average volatility. Then, to apportion overall average cycle effects to industries, region, or firms, we propose to apply beta coefficients based on emissions and location data. In our illustrations to date, we apply industry betas based on rough general estimates of the carbon intensities of those industries. [41]

3.4. ZRE Climate Scenario Illustrations: Applying the Integrated CRST Approach[42]

As noted above, the integrated approach can develop climate scenarios using either stochastic or deterministic methods. We focus here on the stochastic scenarios using the integrated approach which could be applied over both short and long-term time horizons. This stochastic approach includes both firm-level PD TTC Drift and simulations of the Z credit factors subject to climate-related increases in volatility.

We describe the climate scenarios, and after that the portfolio-wide PD, LGD, EAD, and CL estimates. We use an illustrative roughly £140 billion UK/European large-corporate and SME

[40] Alternatively, for projecting the Z paths implied by a macroeconomic-variable (MEV) scenario such as those used in regulatory stress tests, ZRE applies a bridge model jointly calibrated to historical Z and MEV data (transformed into MEV Zs). See, Forest and Aguais, (2019, a) and Aguais and Forest (2023, b) for discussions of our approach for integrating MEV factors with our Z credit factors.

[41] We first applied the illustrative sector carbon intensity betas in, Aguais and Forest (2023, c).

[42] The ZRE version we use in these credit/climate scenarios includes our production Python code which is coupled with our ZRE beta credit/climate module to run these credit/climate scenarios.

portfolio outlined in **Section 6, Appendix II** to develop the various scenarios to assess credit losses including expected and 90% tail losses. For the stochastic scenarios presented here we have run 500 simulations – in implementation we would run more simulations to produce smoother stress scenario loss curves.

The stochastic scenario cases include six based on the NGFS scenarios and a custom one based on a NGFS-type scenario with a more extreme (3-degrees Celsius) GMT rise by 2050. [43]

3.5. Scenario Descriptions and Assumptions

To develop these climate scenarios, we apply two key assumptions to illustrate the approach, for climate volatility effects, we follow the approach applied in Aguais and Forest (2023, b). A discussion of the volatility multiplier specification is included in **Section 5, Appendix I** where we derive the mathematical details for the integrated approach (specifically in **Section 5.5.1**).

In addition to the global vol multipliers, we also apply a set of Z general industry and region beta coefficients (factor loads) as presented in **Table 1**.[44] The proposed integrated approach would ultimately be implemented with a firm-specific climate sensitive PD model along the lines broadly of the ECB approach. Prior to integrating a climate-sensitive PD model as firm-specific TTC drift, the aggregate sector and region betas in **Table 1** are basically proxies for the aggregate sector effects across high and low emission industries. For simplification we assume the beta coefficients remain constant throughout the scenario time spans but they could also be time-dependent in our general framework.

We should be clear about the use of betas in the approach presented here. The betas applied in the scenarios as outlined, are the key assumptions that drive the differential climate effects by sector in relation to the Z model innovations. In **Section 5, Appendix I,** where we derive the overall approach, we also derive firm-specific TTC Drift as a company-level beta that in implementation of the full approach would supplant the sector betas applied here which for the purposes of this paper are average aggregate proxies for individual firms.

[43] The NGFS scenarios and related models used here are discussed in more in Aguais and Forest (2023, b).
[44] For simplicity we aggregate the usual more detailed Z regions into aggregate regions for corporate and FIs. As **Table 1** show, the differences for the industry sector betas are much larger and more important given the role that different sector carbon intensities play in relation to transition risk.

Table 1: Industry and Region Beta Coefficients Applied in Climate Scenarios

Sector	Beta
AEROSPACE & DEFENSE	0.76
AGRICULTURE	1.03
BANKING	0.76
BASIC INDUSTRIES	0.89
BUS & CONSUMER SERVICES	0.76
CHEMICALS AND PLASTIC PRODUCTS	0.89
CONSTRUCTION	1.16
CONSUMER PRODUCTS	0.89
FIN, INSURANCE & REAL ESTATE	0.76
HOTELS & LEISURE	1.03
MACHINERY & EQUIPMENT	0.76
MEDIA	0.76
MEDICAL	0.76
METALS	1.42
MINING	1.42
MOTOR VEHICLES & PARTS	1.16
OIL & GAS	1.82
RETAIL & WHOLESALE TRADE	0.63
TECHNOLOGY	0.76
TRANSPORTATION	1.16
UTILITIES	1.42
CORP REGION	1.02
FI REGION	0.76

Source: See, Aguais and Forest (2023, c) for an explanation of the industry source for the industry/region betas.

3.6. Credit Portfolio Dynamics

Dynamic-credit-portfolio sims estimate the defaults and losses that would occur over time on future portfolios of credit facilities. Static-portfolio sims estimate the losses that would occur over time on today's portfolio of credit facilities. ZRE uses static-portfolio sims in the estimation of term structures of PDs, LGDs, EADs, and ECLs and thereby loan-loss provisions under IFRS 9 or CECL. ZRE uses dynamic-portfolio sims in estimating the time series of losses that would occur under future scenarios including stress-test and CRST ones.

We describe below the ways ZRE implements dynamic-portfolio sims consistent with the conventional approach used generally in regulatory stress tests. In **Section 8, Appendix IV**, we also highlight an alternative dynamic scenario approach that applies one example of an alternative net zero portfolio strategy.

In projecting future portfolios, most scenario estimations including regulatory stress-test ones involve the '*fixed portfolio'* assumption. This convention arises from the observation that, under an unchanging risk appetite, the dynamics of turnover and risk management imply that future portfolios of obligors and facilities would collectively resemble the current ones in terms of TTC (average) risks and exposures*. As a tractable way of implementing this idea, the fixed-portfolio convention freezes the TTC attributes of obligors and facilities to those observed today.* No one believes that future portfolios would remain so rigidly unchanging, but nonetheless this convention could produce results close to those coming from a more realistic depiction of future portfolios consistent with a fixed risk appetite.

Under this convention, the obligors and facilities in the future portfolios become anonymous, no longer identical to those that exist now. In particular, the prospective representative facilities have maturities and limits that remain fixed over time, whereas the current ones have maturities that shrink and limits that may amortize and will eventually vanish. Further, the prospective, representative obligors have TTC PDs that remain the same, whereas the current ones have TTC PDs that evolve probabilistically.

ZRE's fixed-portfolio sims freeze the TTC risk attributes, not the PIT ones. Thus, as the simulated Zs rise and fall, portfolio credit losses vary. And in a deterministic stress scenario in which the Z indices would drop sharply, credit losses would rise substantially.

Occasionally in their credit-loss scenarios, banks include dynamics beyond those implicit in the fixed-portfolio convention. If, for example, a bank has announced an unwinding (building up) of a particular portfolio segment, it would in its baseline and stress scenarios justifiably show exposures to the related entities trending down (up).

3.7. Adaptation and the Evolution of Climate Vols

Global warming creates a race between changes in physical and economic conditions and efforts to adapt to mitigate the harmful effects of those physical and economic changes. If the harmful effects outpace adaptations, the creditworthiness of businesses may well deteriorate. If the adaptations keep abreast of the physical and economic changes, the credit impacts would likely be smaller.

Over the past 33 years for which we have credit-factor Z data, GMT has risen by about 0.8 degree centigrade. This exceeds the increases over the next 30 years projected in virtually all NGFS climate scenarios. In the most severe *Current Policies* scenario, the projected increase is 0.75 degree. Since we have witnessed no obvious signs of material, broad-based climate-related credit deterioration in the past, this suggests that the credit impacts would generally be smaller or localized in the next 30 years except under scenarios much worse than the NGFS ones. Of course, threshold effects including potential physical and socioeconomic tipping points could produce larger impacts than one would infer from experience. The illustrative volatility multiplier we apply depicts climate impacts on factor volatilities that rise at an increasing rate, as a first step in including complex future, non-linear impacts.

3.8 TTC Drift: Individual Firms vs Aggregate Portfolios of Firms

Climate-change scenarios typically show upward trends in costs related to physical damage and transition to greener technologies, with the latter possibly promoted by policies (e.g., carbon taxes) designed to deter businesses from emitting CO2 and other GHGs. Some climate-scenario models including the one developed by the ECB (2021, 2023) assume that some businesses, particularly those with above average exposures to climate risk, only partly pass through these gradually rising costs. For such companies, incomplete cost passthrough causes profitability to trend down, book leverage to increase, and defaults and credit losses to drift up. Alternatively, firms with below-average costs may experience a drift down in PDs. We explain below a way of incorporating this into our climate-scenario models.

Since these effects occur as trends, not as cyclical variations, we introduce them into our climate-scenario models by having the through-the-cycle (TTC) PDs of the exposures in the representative, credit portfolio drift up or down. The modelling of firm-level climate sensitivity as a rising credit trend impact on TTC PDs provides an approach for integrating firm-level effects with credit factors and represents a new contribution in the literature. See below one example of upward TTC drift (**Table 2**). Here the mix of credit grades in the portfolio deteriorates gradually, with the shares of lower risk grades falling and the shares of higher risk grade rising. In this example, the shift produces a change over 2023-2050 in the overall, TTC PD about the same as that projected by the ECB 2021 model in the most severe, Hot House scenario.

Table 2: TTC Risk Grades Without and With TTC Drift

TTC Grade	2023 Shares	2050 Shares No Drift	2050 Shares With Drift
AAA	0.73%	0.73%	0.10%
AA	1.12%	1.12%	1.09%
A+	3.18%	3.18%	1.97%
A	4.20%	4.20%	3.17%
A-	5.36%	5.36%	3.56%
BBB+	8.13%	8.13%	5.90%
BBB	11.46%	11.46%	8.59%
BBB-	12.50%	12.50%	12.18%
BB+	11.51%	11.51%	11.01%
BB	10.62%	10.62%	10.93%
BB-	7.71%	7.71%	11.26%
B+	8.03%	8.03%	7.95%
B	6.04%	6.04%	8.18%
B-	5.44%	5.44%	6.98%
CCC+	2.94%	2.94%	5.63%
CCC	1.06%	1.06%	1.48%

Source: Moody's CreditEdge, NGFS, Z-Risk Engine Calculations

In most of the existing models, TTC drift occurs due to incomplete cost passthrough. However, the aggregate TTC drift can also arise from increases in credit-factor volatilities. In our model, these aggregate volatility impacts are industry and regional.[45] If firms maintain leverage fixed and the vols drift up, then the ratios of leverage to volatility would drift down, producing upward drifting PDs. Alternatively, one can see this occurring due to an increase in the average caused by increased volatility interacting with the convexity of the PD function. We examine this in some climate scenario results presented here.

One should note that an upward drift in the aggregate TTC PDs of the representative portfolio contradicts the fixed-risk-appetite assumption intrinsic to most credit scenarios. One finds a discussion of the determination of a bank's risk appetite in Kerma (2016). If one continues to apply the fixed-risk-appetite assumption, the upward drift in TTC PDs would vanish. This implies that businesses in their financing decisions and banks in their portfolio structuring would act either to maintain leverage unchanged despite incomplete cost passthrough or to reduce leverage by enough to offset rising vols.

The overall implication for banks is that, to assess long-run credit/climate effects on credit portfolios, it is important to apply models that more clearly represent the complex risk

[45] In aggregate credit portfolios subject to rising volatility, the PD convexity relationship means that in long-run credit/climate simulations with rising vol multipliers, we also see rising expected losses. So, the concept of aggregate TTC Drift is similar in spirit to firm-level TTC Drift.

(leverage and volatility) trade-offs they could face due to climate change in long-run scenarios that aren't visible over short time horizons.

3.9. Credit/Climate Scenario Results

We display below results from eight stochastic credit/climate scenarios using the integrated approach (firm TTC Drift proxied by differential sector carbon intensity betas). The stochastic scenarios include six NGFS ones, a 'No Climate' case (the no climate scenario involves excluding both the carbon beta and volatility multiplier effects), and a more extreme scenario implying a 3 degrees Celsius GMT anomaly in 2050. For the stochastic scenarios, we show results in which the rise in vols imply rising TTC PDs and thus an increasing risk appetite and alternative results in which we assume that, due to risk management actions both by firms and credit portfolio managers, the aggregate TTC PDs remain on balance unchanged, consistent with a fixed risk appetite.

In **Figure 9** and **Figure 10**, for the stochastic scenarios, we run 500 simulations each quarter over the time horizon to 2050 for the proposed integrated approach and show climate-change impacts on PDs, ECLs and high-percentile (90%) CLs. The climate-change impacts on ECLs are indicative of effects on accounting provisions. Observe, in **Figure 9**, we show the quarterly PDs start the simulation at roughly 30 bps as the example UK/European portfolio we use has an annual aggregate PD of about 150 bps, consistent broadly with the universe of publicly rated firms. In **Figure 10**, the climate-change impacts on high percentile 90% CLs relative to ECLs are indicative of effects on capital reserves, proxied as UL-ECL. The left-hand panels show the simulation results without aggregate TTC drift adjustments and the right side shows the adjusted results.

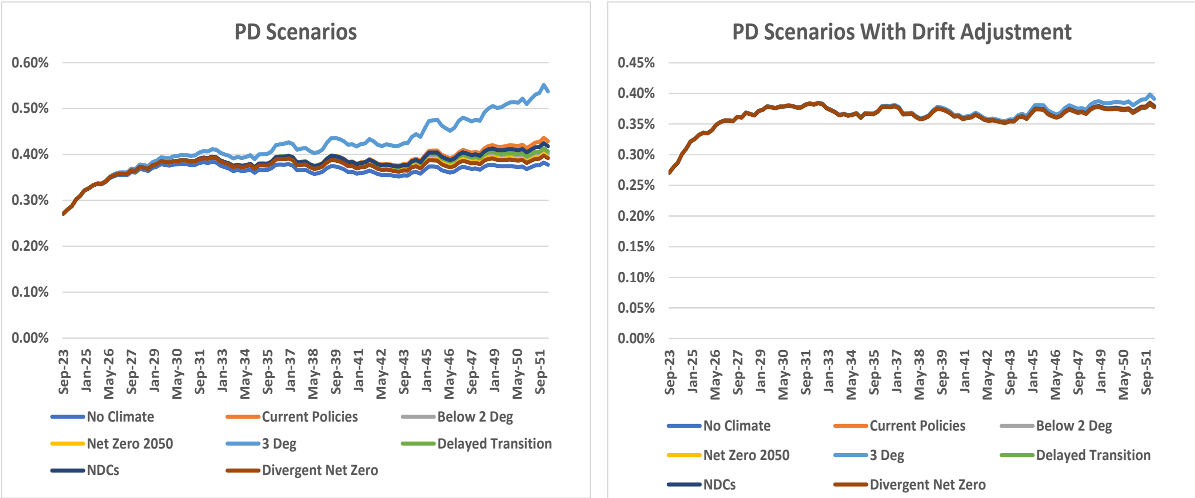

Figure 9: Portfolio Quarterly One-Quarter-Horizon PDs for Stochastic Scenarios

Source: Moody's CreditEdge, NGFS, Z-Risk Engine Calculations

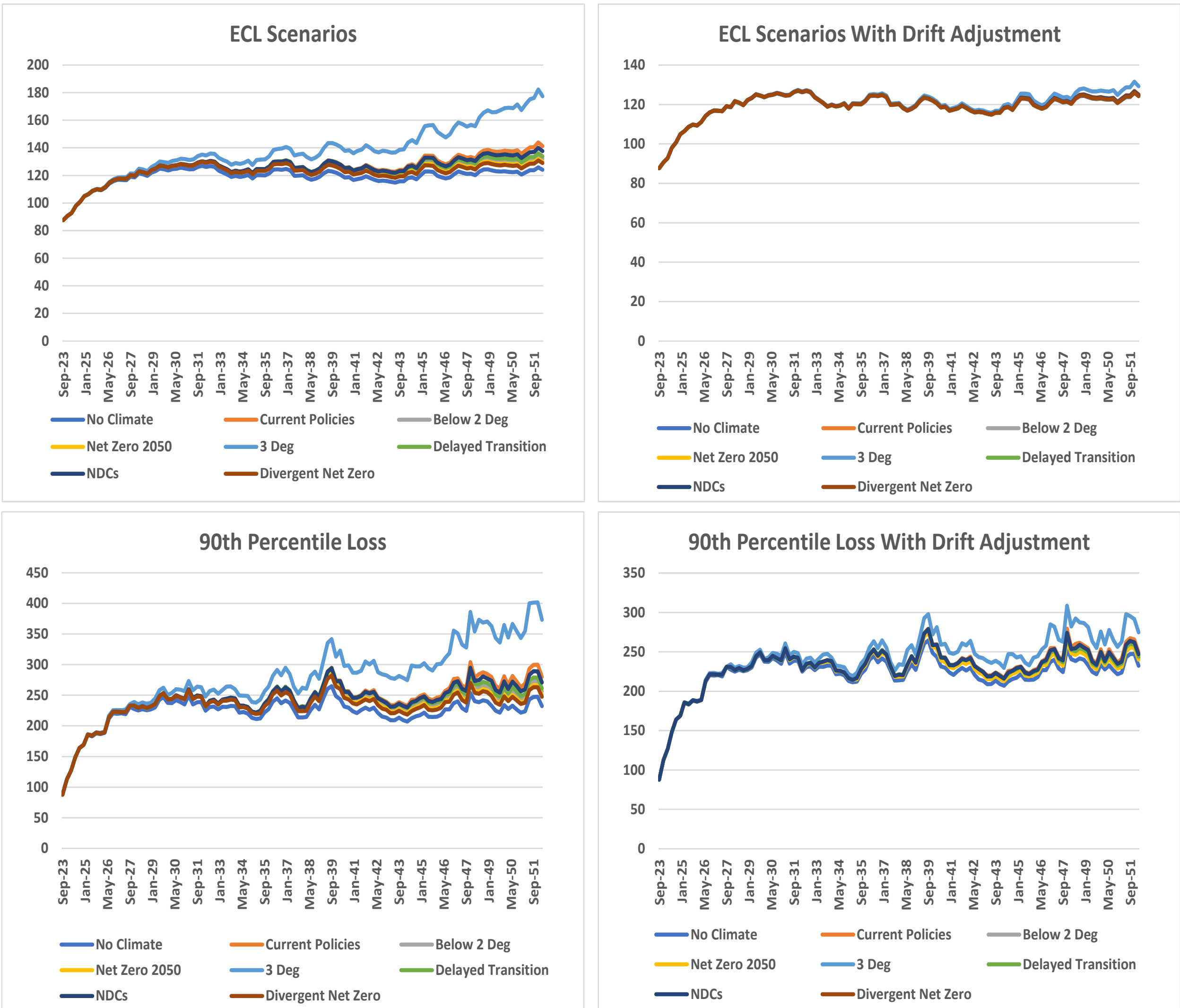

Figure 10: Portfolio Quarterly ECLs and 90th Percentile CLs for Stochastic Scenarios

Source: Moody's CreditEdge, NGFS, Z-Risk Engine Calculations

In **Figures 9** and **10**, for the stochastic scenarios including the No-Climate one, the portfolio-wide PDs, ECLs, and 90th percentile CLs have a concave profile early on, rising at ever diminishing rates and, aside from the random disturbances due to Monte Carlo errors, eventually reverting to a smooth, close to flat or slowly rising trend after about seven or eight years. The early rise reflects the accumulation of shocks, causing the range of possible Z values to increase. A wider range of Z values together with the convexity of the PD functions in the relevant range implies higher portfolio PDs, ECLs, and tail CLs.

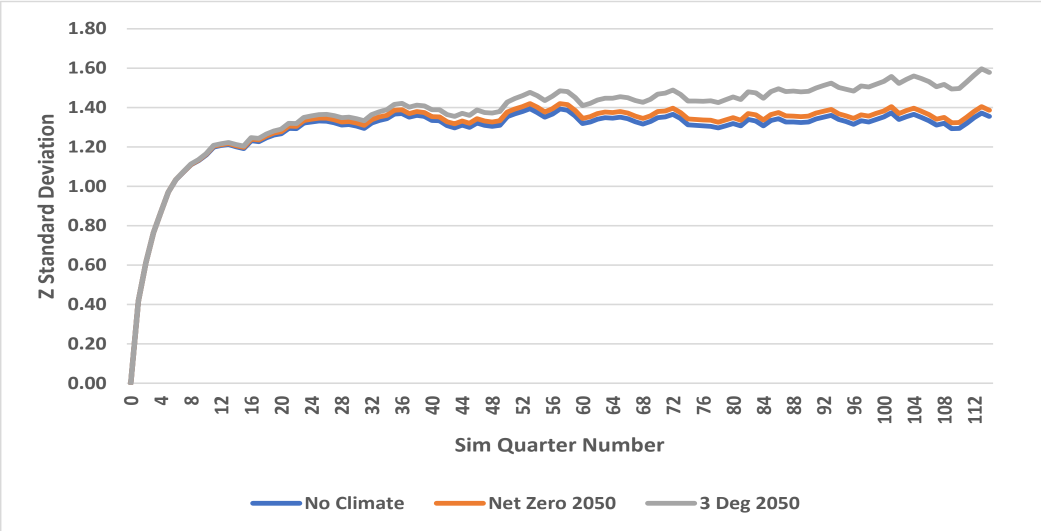

Figure 11: Z Standard Deviations Across Sims for Consumer Products Firms/ UK in Selected Climate Scenarios[46]

Source: Moody's CreditEdge, NGFS, Z-Risk Engine Calculations

We also see that for the climate-change scenarios, which have rising GMTs and vol multipliers, the Z standard deviations continue to trend up relative to the No Climate scenario over the entire simulation period. As shown in **Figure 11**, for an example combined industry sector/region this upward trend leads to upward drifts in aggregate TTC PDs. In the NGFS scenarios, this aggregate drift is smaller. In the 3-degree Celsius scenario, it is much larger. To largely eliminate the aggregate TTC PD drift in a climate scenario, we compute the series of ratios of the quarterly average PDs in the No Climate scenario to those in the climate scenario and enter those ratios as 'drift multipliers' applied to the notional, TTC PDs of each of the facilities. This in turn leads to a rising trend in 'notional' TTC DDs that, together with the rising vols, produces stable values for the simulated average PDs. The rising vols also affect the LGD and EAD results, but, since the relationships to Z are close to linear rather than highly convex, the effects are small.

We call the TTC DDs derived from the TTC PDs in the portfolio file *notional*, since the associated TTC PDs will reconcile with the averages of the simulated PDs in the later periods with stable Z distributions only if the Z vols (and the idiosyncratic vols) remain fixed at their

[46] **Figure 11** uses the combined, weighted-average sector (global consumer products) and region Zs (UK corporate).

historical settings. This happens in the No Climate scenario, but not in the other stochastic scenarios in which the Z vols drift up with GMT. In the presence of upward drifting vols, fixed notional TTC DDs imply fixed TTC leverage, but changing TTC DDs and the negative drift adjustments amount to leverage reductions.

We've found in our trials that the negative aggregate drift adjustments computed as described earlier largely eliminate the rising-Z-vol-induced TTC drifts (see right-hand panels in **Figure 9** and **Figure 10**. One sees that the climate-change-scenario PDs and ECLs are close to the same as the No Climate ones, but some separation remains for 90% tail credit losses. Thus, for a bank holding the illustrative credit portfolio, the negative aggregate drift adjustments reflect assumed, active dynamic risk management in the climate scenarios, which largely eliminates the need for rising loss provisions, but not fully the need for increasing climate-related capital reserves.

4.0. Summary and Comparison of Current Climate Scenarios with the Integrated Approach

This paper describes a new integrated approach for modeling climate effects on credit risk. This is the first approach in the CRST literature to combine ECB-type firm-level models, which describe the gradual intensification of some credit impacts tied to climate change, with credit-risk models depicting the probabilistic occurrence of systematic unexpected shocks, which become increasingly volatile due to rising transition and physical risk under climate change. We implement the ECB-type approach by introducing drift into the TTC PDs of different exposures and the volatility/shock approach by increasing the risk-factor volatilities in line with the climate change depicted in a scenario. The approach builds on Aguais and Forest (2023, a, b, c, d, e, and f). As with most of the existing climate models, the integrated approach here produces projections based on NGFS-type scenarios. We also include in the analysis a custom scenario we show for a scenario where GMT reaches 3 Centigrade by 2050.

In **Table 3**, for reference, we compare the key aspects of current CRST scenarios vs the integrated CRST approach we have proposed here. In **Table 3,** we see a number of ways in which the proposed credit/climate scenario approach reflects fully specified credit models and provides a more flexible and holistic framework as compared to current climate scenarios.

Table 3 Current Mainstream NGFS/ECB Scenarios vs the Integrated Approach*

SCENARIO CHARACTERISTICS	CURRENT MAINSTREAM NGFS/ECB SCENARIO APPROACH	INTEGRATED CREDIT/CLIMATE SCENARIO APPROACH
(1) GENERAL SCENARIO APPROACH:	DETERMINISTIC	***STOCHASTIC & DETERMINSITIC SCENARIO USE CASES***
- TOP-DOWN	NGFS	***NGFS/CUSTOM***
- BOTTOM-UP FIRM SPECIFIC	CLIMATE SENSITIVE CREDIT MODELS	CLIMATE SENSITIVE CREDIT MODELS (TTC DRIFT)
- DEDICATED INDUSTRY SECTOR	NOT INCLUDED	***YES - SECTOR/REGION CREDIT FACTORS***
(2) CREDIT RISK APPROACH:		
- EXPECTED CREDIT LOSSES	CLIMATE-SENSITIVE PD MODEL	CLIMATE-SENSITIVE PD/LGD/EAD
- SYSTEMATIC CREDIT SHOCKS	NOT INCLUDED	***YES - Z SECTOR/REGION CREDIT-FACTOR SIMILATIONS OR DETERMINISTIC ADD-FACTORS***
(3) CLIMATE RISK EFFECTS:		
- TREND EFFECTS	TREND ADJUSTMENTS FOR PHYSICAL/TRANSITION RISKS	TREND ADJUSTMENTS FOR PHYSICAL/TRANSITION RISKS
- VOLATIITY EFFECTS	NOT INCLUDED	***YES - CLIMATE RELATED VOLATILITY ADJUSTMENTS***
(4) SCENARIO TIME STEPS:	5 YEARS OR 1 YEAR IN SOME CASES	***QUARTERLY FOR FACTOR MODELS***
(5) CREDIT PORTFOLIO APPROACH:	UNCLEAR	***STATIC, DYNAMIC OR NET-ZERO MANAGED PORTFOLIO ADJUSTMENTS***
(6) CREDIT/CLIMATE RISK APPETITE:	NOT INCLUED	***YES - USER DETERMINED AGGREGATE PORTFOLIO TTC DRIFT ADJUSTMENTS***

Bolded characteristics of the integrated ZRE CRST approach on the right side of **Table 3 are new contributions that extend the current NGFS/ECB approach.*

To illustrate the application of this novel approach, we have presented climate-change scenarios in which varying amounts of TTC drift occur together with either stochastic or deterministic scenarios of industry and region, credit-factor shocks. In all cases, the TTC drifts and changing risk-factor vols reflect the evolution of climate-related conditions depicted in an NGFS or other IAM/MEV scenario selected by the user. Since banks are starting to work on ECB-like, climate-change-sensitive PD models, the integrated approach presented here allows for projections from such models to determine the firm-level TTC-drifts applied in fully integrated climate-change credit scenarios.

The current implementation of our approach involves climate-scenario projections of the volatilities of amalgamated climate and non-climate shocks. In future implementations, we plan to split the amalgamated shocks into separate non-climate, climate transition-risk, and climate physical-risk shocks, with only the latter two components having climate-change-sensitive volatilities.

For our ongoing research agenda, now that we have specified the details of our proposed integrated CRST framework, we turn to model calibration. Our proposed approach for developing preliminary, statistical calibration of physical (P) and transition (T) climate factors is outlined in **Section 5.6.**

5.0. Appendix I – Detailed Model Specification for Integrated CRST Scenarios: Combining Firm-Specific Climate Sensitivity with Credit Factor Models Subject to Rising Volatility

5.1. Overview and Order of Exposition

This section describes in detail, step-by-step, the ways in which we introduce climate-change sensitivity into Z-Risk Engine's credit risk-factor-based models of probability of default (PD), loss given default (LGD), exposure at default (EAD), and credit-loss (CL). The integrated approach we present is the first to combine firm-level and sector-level climate effects. In doing this, ZRE ideally would draw on the business location and emissions data that others, including the ECB have applied in estimating variations in climate-change credit risks. As ZRE is flexible, the source of the climate-adjusted credit models could be from a bank's own internal development to support regulatory requirements for CRST or from a vendor model that implements a similar approach. [47] *Common to most credit models and research -- and in contrast to much of the work on climate change -- ZRE views credit risk as arising principally from systematic unexpected shocks and not from foreseeable trend changes in economic conditions.*

The order of exposition that we develop in this section is as follows:

First, we discuss:

- ZRE's Existing Climate-Sensitive Model Has Industry and Region Vol Sensitivities Firm-level Credit Model Climate Adjustments – applied as firm-specific TTC Drift, and,
- The extended, integrated approach that Introduces firm-level climate sensitivities.

We present the mathematical details for the integrated CRST approach on a step-by-step basis which follow these six steps:

1. **Step One:** Derive Systematic Credit-Risk Factors
2. **Step Two:** Estimate Models for the Stochastic Evolution of Systematic Factors
3. **Step Three:** Construct Industry-Region Z Factors
4. **Step Four:** Add Climate-Sensitivity to the Z Projections
5. **Step 5:** Run Climate-Sensitive Z Sims
6. **Step Six:** Calculate the PD, LGD, EAD, and Credit Loss Sims for Each of the Facilities in a Portfolio

[47] For banks' current efforts in developing preliminary, climate scenario capabilities to support evolving CRST regulatory deliverables, we highlight some key tasks we suggest for bank's 2024 agenda, see, Aguais (2024).

Section 5.6 completes the section by outlining an approach for developing and applying more refined *physical* and *transition* climate risk factors derived directly from equity markets.

As discussed, ZRE provides two different scenario development *use cases*, firstly for deterministic 'add-factor' shocks (as in Aguais and Forest (2023, e) and is discussed briefly in **Section 7, Appendix III).**

The second and primary scenario use case develops stochastic, simulation-based CRST scenarios that combine firm-level climate adjustments with Z credit factor simulations subject to rising volatility. This is the core approach derived in detail in this section.

5.2. ZRE's Existing Climate-Sensitive Model Has Industry and Region Vol Sensitivities

ZRE's climate-change credit model with industry and region volatility (vol) sensitivities:

- starts with an overall average upward trend in average, credit-risk-factor innovation vols based on an assumed relationship to a relevant climate metric, currently the global mean temperatures (GMTs) in an NGFS or custom climate scenario,
- distributes this overall average, vol trend to industry and region groupings based on industry and region 'betas,' and
- assigns each business obligor in each industry-region segment the same industry-region vol trend as other obligors in that segment.

Under a climate-change scenario, the rising vols lead to a wider range of Monte Carlo simulations (sims) for the credit-cycle factors (Zs) central to the ZRE models. The more volatile Z sims lead to more volatile PD, LGD, EAD, and credit-loss (CLs) sims. And the losses in high-percentile (stress) sims are greater than in the absence of climate change.

This ZRE current climate industry-region approach does not allow for the possibility of differences arising from the varying locations and GHG emissions of obligors within each segment or for rising volatility impacts. This motivates the extended approach, consistent with evolving regulatory requirements focused on firm-level climate impacts.

5.3. Extended, Integrated Approach Introduces Firm-Level Climate Sensitivities

In the extended model, we add these more detailed sensitivities by:

- introducing drifts in the TTC PDs of each firm as implied by a TTC-PD model with inputs affected by the transition and physical risks of a firm, and possibly additionally.
- distributing the global average vol trend directly to individual firms based mainly on their locations, which imply *physical risk*, and their GHG emissions, which relate to *transition risk*.

Under this more detailed approach, the TTC PD drifts could come from bank-developed PD models that are integrated with ZRE. As implied by demand/supply analysis, we expect the drifts from such models to be rising for firms with above average climate-change exposures and decreasing for firms with below average exposures.

The firm-specific vol multiplier extension would involve applying obligor-level beta coefficients to the global average vol multipliers. These obligor betas would have an average value of one. Obligors with greater (lesser) than average exposures to climate-change (physical plus transition) credit risk would have betas above (below) one. For firms without good emissions and location data, we would continue to assign the industry-region betas.

5.4. Initial Calibration Will Apply Bank-Developed Climate-Sensitive PD Models

This leaves open the task of calibrating the climate-change sensitivities, especially the firm-specific PD model inputs required as inputs in the integrated approach. Our ongoing research could determine these key features through empirical estimation perhaps by regressing observed vols on physical- and transition-risk scores.

For the global average vol multiplier, we will initially continue to use the same hypothetical formula found in our existing models. For the obligor betas, we will determine them based on the relative default-distance ($DD = -\Phi^{-1}(PD)$) changes estimated by an existing climate-sensitive, cost-based model. Based on our proposed approach, for each climate scenario, we will:

- covert PDs to DDs by applying the negative of the inverse normal function to PDs,
- calculate, for each company and each scenario time, a delta DD as the difference between the DD under the climate scenario and the DD without climate effects, with this latter DD perhaps best approximated by the DD in the last historical period before the start of the scenario,
- form a global average of the company delta DDs at each scenario time,
- derive, for each company for each scenario time-step, a company beta coefficient as the company delta DD divided by the corresponding global average, and
- compute industry averages of those betas to be used as proxy beta values for companies outside of the estimation sample.

Thus, suppose that, in a climate scenario, a cost-based model projects a fall in DD in 2050 relative to its current (e.g., Dec 2022) value of 0.15 for company A, 0.07 for company B, and 0.10 for the global average company. In this scenario, company A would receive a beta coefficient of 1.5 for 2050 and company B a beta of 0.7. If in the year 2035 in that scenario, the fall in DD was 0.11 for company A and 0.7 for the global average company, company A's beta for 2035 in that scenario would be 1.57 (= 0.11/0.7).

5.5. Mathematical Description of the Current and Integrated ZRE Approaches

We review first some basic features of credit factor models such as ZRE. Then we describe the industry-region-based approach to estimating credit impacts of climate change. After that we present the model extensions leading to a firm-based approach.

5.5.1. Step One: Derive Systematic Credit-Risk Factors

ZRE's models involve industry and region, credit-risk factors that derive from a comprehensive set of listed-company point-in-time (PIT) PDs.[48] One can acquire such PDs from a handful of source models including Moody's CreditEdge. For selected industries and regional groupings, ZRE calculates credit-risk, default-distance-gap (DDGAP) and Z indices and selected variances using the formulas below.

$$\begin{aligned}
DD_{S,t} &= -\Phi^{-1}\left(\underset{i\in S(t)}{\operatorname{med}} PD_{i,t}\right) \\
DDGAP_{S,t} &= DD_{S,t} - \underset{t}{\operatorname{avg}} DD_{S,t} \\
DDGAP_{S,t} &= detrend\left(DDGAP_{S,t}\right) \\
v_S^A &= \underset{t}{\operatorname{var}}\left(DDGAP_{S,t+4} - DDGAP_{S,t}\right) \\
v_S^Q &= \underset{t}{\operatorname{var}}\left(DDGAP_{S,t+1} - DDGAP_{S,t}\right) \\
Z_{S,t} &= DDGAP_{S,t} \Big/ \sqrt{v_S^A}
\end{aligned} \tag{1}$$

Here $DD_{S,t}$ denotes the median Probit-model default distance (DD) inferred from the PDs of companies classified within sector S (= industry I or region R) at time t, $\Phi^{-1}$the inverse normal probability-distribution function, *med* the median function, $DDGAP_{S,t}$ the gap between the median DD for sector S at time t and the historical average median DD for sector S, *avg* the average function, $detrend$ the linear detrend function, v_S^A the variance of annual historical changes in the DDGAPs of sector S, *var* the variance function, v_S^Q the variance of quarterly changes in the DDGAPs of sector S, and $Z_{S,t}$ the value of the Z index for sector S at time t.

5.5.2. Step Two: Estimate Models for the Stochastic Evolution of Systematic Factors

ZRE runs stochastic simulations of quarterly Z paths using mean-reversion momentum (MM) models as specified below.

$$\Delta Z_{S,t+1} = m_{S,1} Z_{S,t} + m_{S,2} \Delta Z_{S,t} + \epsilon_{S,t+1} \tag{2}$$

[48] Over the years we have used all the key vendor, market-based, public-firm default models to calibrate ZRE Zs, including our long-time work with Moody's CreditEdge EDFs and, as well, Kamakura and the University of Singapore Credit Research Initiative (CRI) 'PD' model. See, CRI, (2022). When we ran the RBS Basel II Credit Modelling Team, we also calibrated ZRE to an internal Bloomberg public-firm default model history.

In (2), $\Delta Z_{S,t}$ represents the one-quarter change in the Z for sector S at time t+1, $m_{S,1}$the mean-reversion coefficient (<0) for sector S, $m_{S,2}$the momentum coefficient (>0) for sector S, and $\epsilon_{S,t+1}$the Z innovation for sector S at time t+1. ZRE estimates these MM models for each specified industry and region based on the past monthly time series of Z values (from 1990 to date for CreditEdge).

The MM (or AR2) model formulation extends the legacy approach, which assumes that credit factors evolve as random walks. We add mean reversion due to the observation that recoveries follow recessions. We see this in the historical record of credit losses. We include momentum due to the observation that recessions persist for more than a brief period. The mean-reversion and momentum coefficients are statistically significant in the estimates for almost all industries and regions. The AR2 model explains the historical record much better than current legacy approaches that exclude credit cycles.

5.5.3. Step Three: Construct Industry-Region Factors

Before entering them as cycle variables in facility-level PD, LGD, and EAD models, ZRE combines the industry and region Zs into industry-region ones. Due to data limitations making the tabulation of industries within regions untenable, ZRE forms the composite Z indices as weighted averages of the respective industry and region Zs. The CreditMetrics model, Gupton, Finger and Bhatia (1997), first introduced this use of industry-region composite indices as proxied for industry-within-region ones.

$$\begin{aligned}
DDGAP_{I,R,t} &= w_I\sqrt{v_I^A}Z_{I,t} + (1-w_I)\sqrt{v_R^A}Z_{R,t} \\
v_{I,R}^A &= w_I^2 v_I^A + (1-w_I)^2 v_R^A + 2w_I(1-w_I)\varrho_{I,R}^A\sqrt{v_I^A v_R^A} \\
v_{I,R}^Q &= w_I^2 v_I^Q + (1-w_I)^2 v_R^Q + 2w_I(1-w_I)\varrho_{I,R}^Q\sqrt{v_I^Q v_R^Q} \\
Z_{I,R,t} &= DDGAP_{I,R,t}/\sqrt{v_{I,R}^A}
\end{aligned} \tag{3}$$

In (3), $DDGAP_{I,R,t}$ represents the DDGAP for the industry-I, region-R composite at time t, w_I the weight applied to the industry-I DDGAP (and $(1-w_I)$ applied to the region-R DDGAP), v_I^A the variance of annual changes in DDGAPs for industry I, $v_R^A$the variance of annual changes in DDGAPs for region R, $v_{I,R}^A$the variance of annual changes in DDGAPs for the industry-I, region-R composite, $\varrho_{I,R}^A$the correlation coefficient between annual changes in industry-I and region-R Zs, v_I^Q the variance of quarterly changes in DDGAPs for industry I, $v_R^Q$the variance of quarterly changes in DDGAPs for region R, $v_{I,R}^Q$the variance of quarterly changes in DDGAPs for the industry I, region R composite, $\varrho_{I,R}^Q$the correlation coefficient between quarterly changes in industry-I and region-R Zs and $Z_{I,R,t}$the value of the Z index for the industry-I, region-R composite at time t.

ZRE derives the weights w_I from optimizations finding the best, least-squares fits to the historical quarterly DD changes of listed firms within each industry.

In the above formulations, the MM models for Z sims include no effects of climate change. ZRE applies these models in determining IFRS 9 or CECL provisions and in running both regulatory stress tests and 'No Climate' credit-loss sims. We compare the credit losses in climate sims with the No Climate ones in isolating the effects of climate change under various scenarios. Below we discuss the ways in which we introduce climate-change into ZRE.

5.5.4. Step Four: Add Climate-Sensitivity to the Z Projections

In modeling effects of climate change, ZRE current approach starts by deriving, for a climate scenario, a time series of prospective, global average vol multipliers (VMs). We think of those multipliers as related to a climate-change physical-and-transition risk metric. Currently, we express the prospective series of overall average vol multipliers in a climate scenario as a function of the associated global mean temperature (GMT) path. For now, we are using the hypothetical relationship below:

$$VM_{C,t} = (1 + (GMT_{C,t} - GMTBase)/14.5)^4 \qquad (4)$$

In (4), $VM_{C,t}$ denotes the vol multiplier series for the climate scenario C, $GMT_{C,t}$ the global mean Celsius temperature at time t in climate scenario C, and $GMTBase$ a smoothed GMT value observed in the most recent, historical year without discernable climate-change effects on credit. The fourth power implies that, due to threshold effects, future temperature rises have progressively greater effects on credit volatility, including potential climate-related tipping points. We see below (**Figure 12**) the GMT paths and the associated global vol multipliers for each of the NGFS scenarios and one other that implies a three-degree GMT anomaly in 2050.

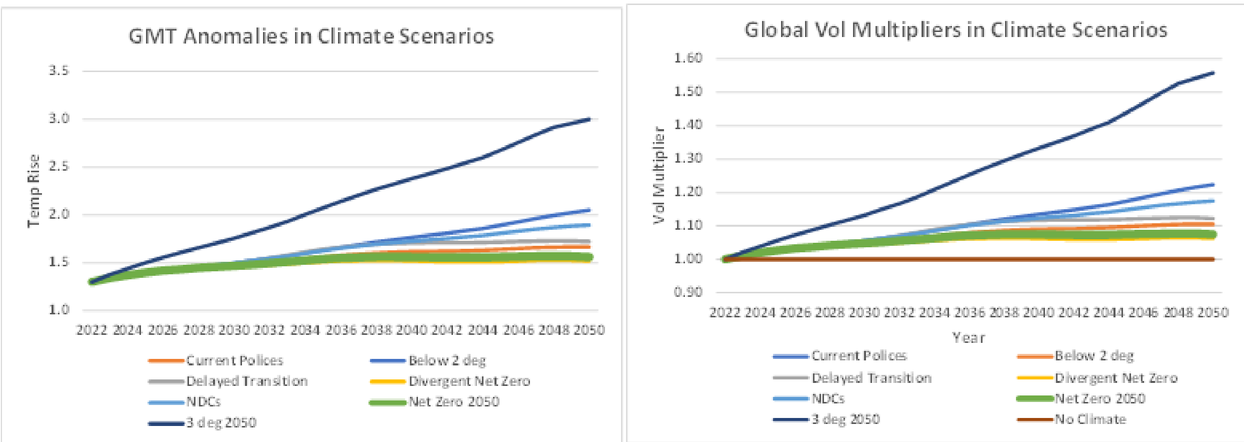

Figure 12: GMT Anomalies and Global Vol Multipliers in Selected Scenarios

Source: Moody's CreditEdge, NGFS, Z-Risk Engine calculations

ZRE next determines, for each industry and region grouping, a beta coefficient reflecting the emissions and locations of an average firm within the industry or region compared with the global average of all firms.[49] The betas amplify (diminish) the global-average vol multiplier in determining the vol multipliers for industries and regions with above-average (below-average) climate-risk exposures. Thus:

$$\begin{aligned} \beta_{I,t} &= c(L_{I,t}, E_{I,t})/c(L_t, E_t) \\ \beta_{R,t} &= c(L_{R,t}, E_{R,t})/c(L_t, E_t) \end{aligned} \quad (5)$$

In (5), *I* denotes an industry, *R* a region, *t* the date, *c* a function determining the climate-risk exposure as related to locations and emissions, $L_{I,t}$ the locations risk score for industry I at time t, $E_{I,t}$ the emissions risk score for industry I at time t, $L_{R,t}$ the locations risk score for region R at time t, $E_{R,t}$ the emissions risk score for region R at time t, and L_t, E_t the global average values of sectoral locations and emissions scores at time t. Thus, L denotes a physical-risk score related to locations of firms within the industry or region and E a transition-risk score related to the GHG emissions attributable to those firms.

Observe that the beta coefficients have time indexes to allow for differential effects of mitigation actions over time. For example, browner industries with above unitary betas initially could act particularly aggressively in mitigating climate risk and therefore have betas that regress towards unity.

The climate-exposure functions referenced above are subjects of ongoing research and so are unavailable at present. Thus, our current projections draw on betas that reflect our judgments of the relative climate exposures of various industries but are broadly consistent with the climate risk literature.

As an initial calibration approach, one might derive the climate betas for individual firms and then, by averaging, for industries and regions from the PD effects that other models derive from emissions and location data and projections of mitigation actions. Note that this would mean using those outside models both for determining TTC drift as well as industry and region volatility betas. As one calibration approach in this case, one could estimate the beta coefficients as follows:

$$\begin{aligned} DD_{e,t,C} &= -\Phi^{-1}\left(PD_{e,t,C}\right) \\ DD_{e,t,NC} &= -\Phi^{-1}\left(PD_{e,t,NC}\right) \\ dDD_{e,t,C} &= \left(DD_{e,t,C} - DD_{e,t,NC}\right) \\ \beta_{e,t,C} &= dDD_{e,t,C} / \underset{e}{avg}\left(dDD_{e,t,C}\right) \\ \beta_{I,t,C} &= \underset{e \in I}{\text{avg}}\, \beta_{e,t,C} \\ \beta_{R,t,C} &= \underset{e \in R}{\text{avg}}\, \beta_{e,t,C} \end{aligned} \quad (6)$$

In the above, $PD_{e,t,C}$ denotes a PD for business entity e at time t under scenario C as obtained from another (cost-based) model, *C* a particular climate scenario, and *NC* the

[49] As explained above, the climate betas we use for now for industry sector and region Zs are proxies until we fully integrate firm-level credit/climate models.

scenario in which climate change has no effect on credit risk. Note that the betas for each industry and region arise by averaging the betas for the firms classified within each industry and region.

Now, for the climate scenario C, ZRE computes, for each industry I and region R, a VM path by multiplying the global average VM path by the applicable beta coefficient.

$$\begin{aligned} VM_{I,t} &= \beta_{I,t} VM_{C,t} \\ VM_{R,t} &= \beta_{R,t} VM_{C,t} \end{aligned} \qquad (7)$$

5.5.5. Step 5: Run Climate-Sensitive Z Sims

ZRE next runs, for each industry I and region R, quarterly Z sims by:

- obtaining series of MM-model residuals for a random selection of past quarters,
- applying the relevant VMs to the randomly selected residuals, and
- entering the rescaled residuals into the MM model and solving iteratively for the related, Zs.

We express this as formulas below.

$$\begin{aligned} q_{s,t+1} &= random(Z\ history\ quarters) \\ \epsilon_{I,s,t+1} &= VM_{I,t+1}\epsilon_I(q_{s,t+1}) \\ \Delta Z_{I,s,t+1} &= m_{I,1}Z_{I,s,t} + m_{I,2}\Delta Z_{I,s,t} + \epsilon_{I,s,t+1} \\ Z_{I,s,t+1} &= \Delta Z_{I,s,t+1} + Z_{I,s,t} \\ \epsilon_{R,s,t+1} &= VM_{R,t+1}\epsilon_R(q_{s,t+1}) \\ \Delta Z_{R,s,t+1} &= m_{R,1}Z_{R,s,t} + m_{R,2}\Delta Z_{R,s,t} + \epsilon_{R,s,t+1} \\ Z_{R,s,t+1} &= \Delta Z_{R,s,t+1} + Z_{R,s,t} \end{aligned} \qquad (8)$$

Here $q_{s,t+1}$denotes a randomly selected historical quarter to be used in drawing MM-model residuals for sim s at time t+1, $\epsilon_{I,s,t+1}$ a Z innovation for industry I in sim s at time t+1, $VM_{I,t+1}$ vol multiplier for industry I at time t+1, $\epsilon_{I,s,h}$ the MM-model residual for industry I in sim s in past quarter q, $\Delta Z_{I,s,t+1}$ the one-quarter change in the value of the Z index for industry I in sim s at time t+1, $m_{I,1}$the mean-reversion coefficient for industry I, $m_{I,2}$ the momentum coefficient for industry I, $Z_{I,s,t}$ the value of the Z index for industry I in sim s at time t, $\epsilon_{R,s,t+1}$ the Z innovation for region R in sim s at time t+1, $VM_{R,t+1}$ the vol multiplier in for region R at time t+1, $\epsilon_{R,s,h}$ the MM-model residual for region R in sim s in past quarter q, $\Delta Z_{R,s,t+1}$ the one-quarter change in the value of the Z index for region R in sim s at time t+1, $m_{R,1}$ the mean-reversion coefficient for region R, $m_{R,2}$ the momentum coefficient for region R and $Z_{R,s,t}$ the value of the Z index for region R in sim s at time t. The random sequence of historical quarters used in choosing innovations in a sim are the same for each industry and region. This ensures that the sims embody cross-sector correlations.

Next, ZRE applies formulas (3) in combining the industry and region Z sims for each permissible industry-region pair to obtain the industry-region-composite Z ('ZIR') sims.

These ZIR sims provide the credit factor inputs into the PD, LGD, and EAD models that produce the facility-level loss sims. As needed for these facility sims, ZRE imports, from databases and files, the credit-facility descriptive data and the PD-, LGD-, and EAD-model parameters (see **Table 4 and Table 5**).

Table 4: Excerpt from Sample Portfolio File

FAC #	Portfolio	TTC Grade	TTC PD	Product	Current Maturity	Limit	EU	TTC LGD	TTC CCF	FCF	Region	Industry
1	SME	BB	0.72%	Term	6.00	3.0	100.00%	30%	100%	100%	GERMANY	MEDIA
2	SME	BBB-	0.27%	Contingent	1.00	5.0	10.00%	40%	70%	25%	FRANCE	BUSINESS AND CONSUMER SERVICES
3	SME	A	0.05%	Term	5.50	3.0	100.00%	30%	100%	100%	FRANCE	BUSINESS AND CONSUMER SERVICES
4	SME	A-	0.06%	Term	0.75	7.0	100.00%	50%	100%	100%	GERMANY	BUSINESS AND CONSUMER SERVICES
5	LC	BBB-	0.27%	Revolving	2.00	50.0	50.00%	10%	70%	100%	SPAIN	CONSUMER PRODUCTS
6	SME	BBB	0.17%	Term	5.25	2.0	100.00%	30%	100%	100%	ITALY	BUSINESS AND CONSUMER SERVICES
7	SME	B	4.04%	Term	3.00	3.0	100.00%	30%	100%	100%	ITALY	CONSTRUCTION
8	SME	BB+	0.51%	Revolving	0.75	7.0	50.00%	20%	20%	100%	FRANCE	FINANCE, INSURANCE AND REAL ESTATE
9	LC	BB-	1.49%	Backstop	0.50	50.0	0.00%	30%	70%	100%	SPAIN	UTILITIES
10	SME	B+	2.42%	Term	1.00	10.0	100.00%	30%	100%	100%	GERMANY	FINANCE, INSURANCE AND REAL ESTATE
11	LC	BBB-	0.27%	Revolving	6.50	70.0	20.00%	40%	20%	100%	UK	MOTOR VEHICLES AND PARTS
12	SME	BB+	0.51%	Term	4.75	7.0	100.00%	40%	100%	100%	FRANCE	HOTELS AND LEISURE
13	SME	BBB-	0.27%	Term	1.75	10.0	100.00%	70%	100%	100%	SPAIN	BUSINESS AND CONSUMER SERVICES
14	SME	CCC	22.63%	Term	1.25	5.0	100.00%	20%	100%	100%	FRANCE	FINANCE, INSURANCE AND REAL ESTATE
15	SME	BB	0.72%	Term	5.75	7.0	100.00%	20%	100%	100%	GERMANY	RETAIL AND WHOLESALE TRADE
16	SME	B+	2.42%	Revolving	2.00	2.0	50.00%	40%	30%	100%	GERMANY	AGRICULTURE
17	SME	CCC+	11.03%	Term	2.00	3.0	100.00%	20%	100%	100%	GERMANY	CONSTRUCTION
18	LC	BB	0.72%	Backstop	0.75	40.0	0.00%	20%	70%	100%	ITALY	RETAIL AND WHOLESALE TRADE
19	SME	B-	6.61%	Contingent	1.00	7.0	20.00%	30%	20%	25%	ITALY	AGRICULTURE
20	LC	BBB-	0.27%	Backstop	0.50	70.0	0.00%	30%	45%	100%	GERMANY	HOTELS AND LEISURE
21	LC	BB	0.72%	Revolving	0.75	70.0	10.00%	30%	20%	100%	SPAIN	TECHNOLOGY
22	LC	BB	0.72%	Revolving	1.00	40.0	80.00%	30%	45%	100%	SPAIN	BUSINESS AND CONSUMER SERVICES
23	SME	BBB	0.17%	Term	3.50	5.0	100.00%	40%	100%	100%	GERMANY	MEDICAL
24	SME	B	4.04%	Term	5.75	5.0	100.00%	20%	100%	100%	ITALY	AGRICULTURE
25	SME	BB	0.72%	Revolving	4.75	5.0	50.00%	50%	30%	100%	SPAIN	BASIC INDUSTRIES
26	SME	BBB	0.17%	Term	3.50	5.0	100.00%	30%	100%	100%	GERMANY	HOTELS AND LEISURE
27	SME	CCC+	11.03%	Contingent	1.50	5.0	50.00%	20%	70%	25%	UK	BUSINESS AND CONSUMER SERVICES
28	SME	BBB+	0.12%	Term	0.25	3.0	100.00%	60%	100%	100%	UK	TRANSPORTATION
29	SME	B-	6.61%	Term	6.25	5.0	100.00%	60%	100%	100%	SPAIN	MEDICAL
30	SME	BB-	1.49%	Revolving	3.75	5.0	60.00%	30%	20%	100%	UK	CHEMICALS AND PLASTIC PRODUCTS
31	SME	A-	0.06%	Term	1.00	3.0	100.00%	30%	100%	100%	FRANCE	MACHINERY AND EQUIPMENT
32	LC	BBB-	0.27%	Revolving	4.25	30.0	0.00%	30%	45%	100%	NORDIC STATES	MEDICAL
33	LC	BBB-	0.27%	Term	1.50	50.0	100.00%	30%	100%	100%	BENELUX	HOTELS AND LEISURE
34	LC	BBB	0.17%	Revolving	0.75	50.0	50.00%	60%	20%	100%	GERMANY	MEDICAL
35	SME	BBB	0.17%	Contingent	0.75	3.0	80.00%	40%	20%	25%	FRANCE	RETAIL AND WHOLESALE TRADE
36	SME	B-	6.61%	Revolving	2.75	10.0	0.00%	30%	30%	100%	UK	BUSINESS AND CONSUMER SERVICES
37	SME	A	0.05%	Term	0.75	5.0	100.00%	20%	100%	100%	SPAIN	BUSINESS AND CONSUMER SERVICES
38	SME	B	4.04%	Revolving	0.50	7.0	20.00%	40%	70%	100%	GERMANY	FINANCE, INSURANCE AND REAL ESTATE
39	SME	B+	2.42%	Revolving	0.75	5.0	50.00%	30%	20%	100%	GERMANY	OIL AND GAS
40	LC	A+	0.04%	Revolving	1.50	50.0	60.00%	40%	20%	100%	ITALY	BUSINESS AND CONSUMER SERVICES

Source: Author's assumptions, used to develop the illustrative credit portfolio

Table 5: Excerpt from Sample Parameters File*

Sector	Z_0	dZ_0	weight	Z_Norm	V_A	V_Q	m1	m2	sigma
AEROSPACE AND DEFENSE	-0.01	0.35	0.38	-0.32	0.04	0.01	-0.10	0.24	0.42
AGRICULTURE	-0.16	0.22	0.29	-0.37	0.03	0.01	-0.08	0.13	0.45
BANKING	1.16	0.39	0.31	-0.27	0.01	0.00	-0.06	0.30	0.39
BASIC INDUSTRIES	1.01	0.04	0.32	-0.40	0.03	0.00	-0.06	0.24	0.42
BUSINESS AND CONSUMER SERVICES	-0.25	0.11	0.43	-0.41	0.03	0.00	-0.06	0.21	0.41
CHEMICALS AND PLASTIC PRODUCTS	-0.41	0.00	0.36	-0.30	0.02	0.00	-0.09	0.22	0.43
CONSTRUCTION	0.80	0.26	0.28	-0.28	0.03	0.01	-0.10	0.28	0.40
CONSUMER PRODUCTS	0.24	0.32	0.44	-0.35	0.02	0.00	-0.08	0.29	0.39
FINANCE, INSURANCE AND REAL ESTATI	0.07	0.32	0.35	-0.13	0.00	0.00	-0.08	0.35	0.39
HOTELS AND LEISURE	-0.10	0.32	0.47	-0.44	0.03	0.00	-0.05	0.24	0.40
MACHINERY AND EQUIPMENT	0.70	0.17	0.30	-0.31	0.03	0.01	-0.09	0.25	0.43
MEDIA	0.04	-0.10	0.36	-0.62	0.04	0.01	-0.06	0.28	0.37
MEDICAL	-0.79	0.03	0.34	-0.52	0.03	0.01	-0.06	0.00	0.47
METALS	1.26	0.26	0.27	-0.34	0.04	0.01	-0.09	0.24	0.43
MINING	0.21	0.04	0.72	-0.37	0.04	0.01	-0.08	0.24	0.40
MOTOR VEHICLES AND PARTS	0.02	0.37	0.23	-0.29	0.04	0.01	-0.11	0.31	0.40
OIL AND GAS	1.04	0.44	0.59	-0.48	0.04	0.01	-0.11	0.26	0.41
RETAIL AND WHOLESALE TRADE	0.03	0.26	0.36	-0.33	0.02	0.00	-0.08	0.25	0.42
TECHNOLOGY	0.21	0.03	0.46	-0.50	0.04	0.01	-0.06	0.17	0.44
TRANSPORTATION	0.42	0.07	0.40	-0.26	0.03	0.01	-0.11	0.28	0.40
UTILITIES	0.97	0.22	0.48	-0.54	0.02	0.00	-0.07	0.19	0.42
ASIA	0.60	0.11		-0.34	0.03	0.01	-0.10	0.28	0.40
ASIA FI	0.59	0.23		-0.26	0.02	0.00	-0.08	0.23	0.42
BENELUX	-0.30	0.33		-0.54	0.04	0.01	-0.06	0.25	0.40
BENELUX FI	-0.34	0.15		-0.18	0.01	0.00	-0.10	0.15	0.44
FRANCE	-0.19	-0.20		-0.43	0.04	0.01	-0.06	0.21	0.42
FRANCE FI	-0.88	0.18		-0.13	0.00	0.00	-0.09	0.10	0.46
GERMANY	-0.18	-0.22		-0.83	0.04	0.01	-0.03	0.33	0.36
GERMANY FI	0.18	0.09		-0.29	0.01	0.00	-0.05	0.24	0.40
ITALY	-0.30	0.05		-0.29	0.06	0.01	-0.13	0.28	0.40
ITALY FI	1.16	0.50		-0.22	0.01	0.00	-0.11	0.14	0.47
LATIN AMERICA	-0.06	0.13		-0.74	0.05	0.01	-0.06	0.02	0.50
LATIN AMERICA FI	0.43	0.15		-0.47	0.02	0.01	-0.09	0.02	0.61
MIDDLE EAST & AFRICA	0.86	0.37		-0.60	0.03	0.01	-0.06	0.03	0.51
MIDDLE EAST & AFRICA FI	1.43	0.33		-0.31	0.01	0.00	-0.06	0.02	0.48
NORDIC STATES	-0.33	-0.21		-0.41	0.05	0.01	-0.07	0.28	0.39
NORDIC STATES FI	-0.51	0.10		-0.23	0.01	0.00	-0.05	0.15	0.42
NORTH AMERICA	0.03	0.20		-0.34	0.03	0.01	-0.09	0.22	0.42
NORTH AMERICA FI	0.86	0.23		-0.18	0.01	0.00	-0.07	0.30	0.40
PACIFIC	0.74	0.02		-0.72	0.03	0.01	-0.08	0.09	0.44
PACIFIC FI	0.06	-0.04		-0.22	0.01	0.00	-0.08	0.11	0.44
REST OF EUROPE	0.42	0.55		-0.43	0.04	0.01	-0.07	0.27	0.40
REST OF EUROPE FI	0.77	0.66		-0.23	0.01	0.00	-0.06	0.07	0.48
SPAIN	-0.44	0.01		-0.45	0.06	0.01	-0.08	0.14	0.44
SPAIN FI	1.12	0.54		-0.28	0.01	0.00	-0.06	0.00	0.47
UK	-0.21	-0.17		-0.46	0.03	0.01	-0.06	0.30	0.38
UK FI	-0.62	0.51		-0.19	0.00	0.00	-0.06	0.20	0.43

Source: Moody's CreditEdge, NGFS, Z-Risk Engine Calculations

This Table is an output file from ZRE that shows a standard set of Region Z segments (both industry sectors and regions are customized for each bank's credit portfolio characteristics). In the portfolio analysis we present for the UK/Europe credit portfolio, we use a smaller set of Region Zs as shown for the portfolio segmentations in **Section 6 - Appendix II.*

5.5.6. Step Six: Calculate the PD, LGD, EAD, and Credit Loss Sims for Each of the Facilities in a Portfolio

In calculating the PDs for each facility f in each sim s for each sim quarter ending at time t, ZRE applies a Probit model.

$$
\begin{aligned}
I &= I(f) \\
R &= R(f) \\
DD_{Q,f}^{TTC} &= -\Phi^{-1}\left(PD_f^{TTC}/4\right) \\
\rho_{I,R}^{A} &= v_{IR}^{A} \\
\rho_{I,R}^{Q} &= \frac{v_{IR}^{Q}}{v_{IR}^{Q} + (1 - v_{IR}^{A})/4} \\
PD_{f,s,t} &= \Phi\left(\frac{-\left(DD_{Q,f}^{TTC} + \sqrt{\rho_{I,R}^{A}}\left(Z_{I,R,s,t} - Z_{n,I,R}\right)\right)}{\sqrt{1-\rho_{I,R}^{Q}}}\right)
\end{aligned}
\qquad (9)
$$

Here I = I(f) and R = R(f) indicate that ZRE sets I to the primary industry and R to the primary region of the principal obligor of facility f. $DD_{Q,f}^{TTC}$ denotes the through-the-cycle (TTC) one-quarter DD of the principal obligor of facility f, $PD_f^{TTC}$the one-year-horizon TTC PD of the principal obligor of facility f, $\rho_{I,R}^{A}$the systematic risk proportion of total annual ΔDD variance, $\rho_{I,R}^{Q}$the systematic risk proportion of total quarterly ΔDD variance, $PD_{f,s,t}$ the one-quarter PD of the principal obligor of facility f in sim s at time t, and $Z_{n,I,R}$ the Z value that yields Z-conditional PDs the same as the TTC PDs for obligors within the industry-I, region-R composite sector. The Z norm values are negative, due to the convexity of the PD function in the relevant range. That convexity implies that the TTC PD, which is the average PD across all states of the cycle, exceeds the PD at the average (Z=0) state of the cycle.

Next ZRE calculates the LGDs in each sim using the formulas in (10), which apply a Tobit model in producing the expected value of LGD conditional on the simulated Z value. Following a common convention for reducing the computation burden, the sims include conditional expected values and not every possible LGD realization.

$$
\begin{aligned}
m_{0.f} &= m_0(LGD_f^{TTC}) \\
m_{f,s,t} &= m_{0,f} + m_Z Z_{I,R,s,t} \\
\sigma_{f,s,t} &= exp\left(s_0 + s_Z Z_{I,R,s,t}\right) \\
ELGD_{f,s,t} &= \Phi\left(-\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right) + m_{f,t}\left(\Phi\left(\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right) - \Phi\left(-\frac{m_{f,s,t}}{\sigma_{f,s,t}}\right)\right) \\
&+ s_{f,t}\left(\phi\left(-\frac{m_{f,s,t}}{\sigma_{f,s,t}}\right) - \phi\left(\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right)\right)
\end{aligned}
\qquad (10)
$$

Here $m_{0.f}$ denotes the constant term in the formula for the Tobit central tendency parameter, LGD_f^{TTC} the TTC LGD of the facility f, m_Z the coefficient applied to Z in the central-tendency formula, s_0 the constant term in the formula for the spread parameter, and s_Z the coefficient applied to the Z in that formula. $m_{f,s,t}$represents the mean of the normal distribution in the Tobit model in sim s at time t and $\sigma_{f,s,t}$ the related standard deviation, Φ

the normal distribution function, and ϕ the normal density function. The parameters come from past empirical research, although a bank may choses to revise them based on a its own experience. Note that, with a simple recalibration, the lookup for the central-tendency constant term may take the downturn LGD rather than the TTC one as its argument.

ZRE calculates the EADs in each sim using the formulas below, which apply a Probit model for the credit-conversion factor (CCF).

$$\begin{aligned} c_{0.f} &= \Phi^{-1}(CCF_f^{TTC}) \\ CCF_{f,s,t} &= \Phi\left(c_{0,f} + c_Z Z_{I,R,s,t}\right) \\ EEAD_{f,s,t} &= \left(EU_f + \left(1 - EU_f\right)CCF_{f,s,t}\right)FCF_f L_{f,t} \end{aligned} \qquad (11)$$

Here $c_{0.f}$ denotes the constant term in the CCF formula, CCF_f^{TTC} the facility's TTC CCF from the portfolio file, c_Z the coefficient applied to Z in the CCF formula, $EEAD_{f,s,t}$ the conditional expected value of EAD for facility f in sim s at time t, EU_f the expected utilization of the facility f, FCF_f the funding conversion factor for facility f, and $L_{f,t}$ the limit for facility f at time t. The FCF has a value of one for cash facilities and typically below one for contingent (e.g., documentary trade credit, bond discount) facilities.

The CL sims then arise from an identify.

$$CL_{f,s,t} \quad = PD_{f,s,t} \cdot ELGD_{f,s,t} \cdot EEAD_{f,s,t} \qquad (12)$$

To obtain a reasonable representation of the credit-loss distributions, one would run many sims, perhaps more than a thousand. For a climate scenario, C, one gets the loss sims for a particular portfolio, P, of facilities by summing the loss sims for the facilities within the portfolio. P could represent the total portfolio, an industry or regional subset, all large-corporate facilities, all SMEs, or other identifiable segments.

$$CL_{C,P,s,t} \quad = \sum_{f \epsilon P} CL_{C,f,s,t} \qquad (13)$$

From these results, one can compute various statistics including the expected value, standard deviation, and various quantiles.

$$\begin{aligned} ECL_{C,P,,t} &= \operatorname*{avg}_s CL_{C,P,s,t} \\ CL_{C,P,t}^N &= \operatorname*{NP}_s CL_{C,P,s,t} \end{aligned} \qquad (14)$$

Here $ECL_{C,P,,t}$ denotes the expected credit loss in climate scenario C for portfolio P at time t, $CL_{C,P,t}^N$ the Nth percentile loss in climate scenario C for portfolio P at time t, and NP the Nth percentile function.

To get the climate-scenarios impacts, one merely subtracts the same statistics from the No Climate scenario.

$$
\begin{aligned}
ECLD_{C,P,,t} &= ECL_{C,P,,t} - ECL_{NC,P,,t} \\
CLD^{N}_{C,P,t} &= CL^{N}_{C,P,t} - CL^{N}_{NC,P,t}
\end{aligned}
\tag{15}
$$

Here the appended D indicates the difference between the statistic's value in the C scenario and its value in the NC scenario.

5.5.7. Model Extensions: Add Company-Level Climate-Vol Sensitivity

Instead of using averages of obligor betas in producing vol multiplier for each industry and region as in formulas (7), ZRE instead could use the individual obligor betas in the formula (16) below in determining the vol multipliers applicable to each legal entity e with the beta coefficients $\beta_{e,t}$.

$$VM_{e,t} \quad = \beta_{e,t} \cdot VM_{C,t} \tag{16}$$

Next, for each entity e, ZRE runs sims for the entity's primary industry $I = I(e)$ and primary region $R = R(e)$.

$$
\begin{aligned}
q_{s,t+1} &= random(Z\ history\ quarters) \\
\epsilon_{I,s,t+1} &= VM_{e,t+1}\epsilon_{I}(q_{s,t+1}) \\
\Delta Z_{I,s,t+1} &= m_{I,1}Z_{I,s,t} + m_{I,2}\Delta Z_{I,s,t} + \epsilon_{I,s,t+1} \\
Z_{I,s,t+1} &= \Delta Z_{I,s,t+1} + Z_{I,s,t} \\
\epsilon_{R,s,t+1} &= VM_{e,t+1}\epsilon_{R}(q_{s,t+1}) \\
\Delta Z_{R,s,t+1} &= m_{R,1}Z_{R,s,t} + m_{R,2}\Delta Z_{R,s,t} + \epsilon_{R,s,t+1} \\
Z_{R,s,t+1} &= \Delta Z_{R,s,t+1} + Z_{R,s,t}
\end{aligned}
\tag{17}
$$

Observe that the formulas (17) differ from the earlier ones at (8) only in the application of entity vol multipliers in place of industry and region ones. Also, ZRE performs these sims for each entity rather than for each industry and region. This entails a heavier computational burden. Suppose a credit portfolio includes 10,000 legal entities, each classified within one of twenty-five industries and one of ten regions. Suppose, further, that we choose to run 1,000 Monte Carlo sims extending 115 quarters and that we have company specific climate-risk scores for 2,000 obligors and must use industry-based proxies for the remaining 8,000 (mostly SME companies). Under the existing industry-region vol-multiplier approach, this would entail 35,000 (= 25 x 1,000 + 10 x 1,000) Monte Carlo sims extending 115 quarters. Under the obligor approach, this would entail 2,035,000 million (2,000 x 2 x 1,000+ 35,000) sims extending 115 quarters.

ZRE now applies formulas (3) in producing the industry-region-composite sims for each entity. To emphasize the dependency on the legal entity of the facility, we will use the notation $Z_{e,s,t}$ to denote the value of the industry-region ZIR factor for entity e in sim s at time t. These sims involve entity e's vol multipliers applied in running sims for entity e's primary industry and region.

$$
\begin{aligned}
I &= I(e(f)) \\
R &= R(e(f)) \\
DD_{Q,f}^{TTC} &= -\Phi^{-1}\left(PD_f^{TTC}/4\right) \\
\rho_f^A &= v_{IR}^A \\
\rho_f^Q &= \frac{v_{I(e),R(e)}^Q}{v_{IR}^Q + (1 - v_{IR}^A)/4} \\
PD_{f,s,t} &= \Phi\left(\frac{-\left(DD_{Q,f}^{TTC} + \sqrt{\rho_f^A}\left(Z_{e(f),s,t} - Z_{n,e(f)}\right)\right)}{\sqrt{1-\rho_f^Q}}\right)
\end{aligned}
\tag{18}
$$

Similarly, the LGD and EAD formulas apply the entity ZIR factors.

$$
\begin{aligned}
m_{0.f} &= m_0(LGD_f^{TTC}) \\
m_{f,s,t} &= m_{0,f} + m_Z Z_{e(f),s,t} \\
\sigma_{f,s,t} &= exp\left(s_0 + s_Z Z_{e(f),s,t}\right) \\
ELGD_{f,s,t} &= \Phi\left(-\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right) + m_{f,t}\left(\Phi\left(\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right) - \Phi\left(-\frac{m_{f,s,t}}{\sigma_{f,s,t}}\right)\right) \\
&\quad + s_{f,t}\left(\phi\left(-\frac{m_{f,s,t}}{\sigma_{f,s,t}}\right) - \phi\left(\frac{1 - m_{f,s,t}}{\sigma_{f,s,t}}\right)\right) \\
c_{0.f} &= \Phi^{-1}(CCF_f^{TTC}) \\
CCF_{f,s,t} &= \Phi\left(c_{0,f} + c_Z Z_{e,s,t}\right) \\
EEAD_{f,s,t} &= \left(EU_f + (1 - EU_f)CCF_{f,s,t}\right)FCF_f L_{f,t}
\end{aligned}
\tag{19}
$$

The remaining calculations are the same as in the industry- and region-based approach (see formulas (12) to (15)). As mentioned earlier, some cost-based models of climate-sensitive TTC PDs produce estimates that show the PDs drifting up or down over time for selected businesses. The climate sensitive ZRE model can introduce these time series of TTC PDs into its scenarios by means of a time series of portfolio files. In the trials presented thus far, the TTC PDs of the different representative obligors have been constant and so there was only one portfolio-attribute file, not a time series. However, in the integrated model, we would include TTC drifts as indicated in a series of portfolio files.

Be aware, however, that upward drifts in risk-factor volatilities already produce upward drifts in aggregate TTC PDs. This occurs due to the PD function being convex in the relevant range. Since the cost-based external-model estimates typically exclude effects of risk-factor volatility, one might question whether combining the TTC drifts from two separate sources yields a reliable result. Indeed, one might also question whether firms on their own or as compelled by creditors would take risk-reducing actions such as deleveraging so as to mitigate or even negate aggregate TTC drift. We plan to explore this question as part of our ongoing research agenda.

5.6. Model Calibration Research Agenda: Developing Climate Physical and Transition Risk Factors

As highlighted earlier one could develop transition (T) and physical (P) climate-change risk factors from structured portfolios of market-value-related indicators. Many of the existing studies in this vein apply this idea using equity prices. Here, we summarize one potential approach for overall model calibration, to create climate risk-factors relevant to credit, we propose building them based on Merton-model, DDs (= minus normal inverse of PIT PDs) of listed firms. *We have started preliminary research on this suggested approach using climate data from a leading climate data vendor.*

We could create the credit-risk T factor as the median or average DD of companies with high emissions minus the median or average DD of companies with low emissions. Analogously, we could create the P factor as the median or average DD of companies with high physical risk based on location minus the median or average DD of companies with low physical risk.

After developing the past values of the factors, we could introduce them into ZRE by:

- running regressions of industry and region Zs on T and P Zs,
- using those regression results to split Zs into climate and non-climate components, where the climate component is the value implied by the T and P factors and the non-climate one the residual,
- developing relationships between NGFS scenario data and T and P Zs,
- applying those relationships in running NGFS climate stress tests,
- creating separate climate and non-climate MM models with the climate innovations possibly expanding in variance over time as climate transition and physical risks grow (and possibly reverting at some point), and,
- using those MM models in Monte Carlo sims for estimating IFRS 9 ECLs.

Observe that this proposal for further research extends the currently implemented volatility-multiplier approach. The existing approach applies Z factors that reflect the combined influence of climate and non-climate shocks. And in projections, we assume that the volatility of such shocks increases with climate change because of the increasing volatility of the climate component. Under the proposed approach, we could split the Z factors into climate and non-climate components and further split the climate component into T and P factors. We then assume that the non-climate vols remain constant and the T and P factor vols increase over time due to climate change. Thus, the proposed approach represents an elaboration of the existing one.

6.0. Appendix II: UK/European Credit Portfolio Used in the Illustrative Credit/Climate Scenario Analysis

The illustrative UK/European credit portfolio characteristics in the credit/climate scenarios presented here are summarized in the following tables. The portfolio includes loans to both large-corporate and SME firms in a variety of industries and countries and with varying credit grades, see tables below.

Portfolio Size	
Limit (million)	€151,818
Facility Count	10,002

Facility-type Composition (limits)	
Term	36.40%
Revolving	39.59%
Backstop	20.76%
Contingent	3.25%

Industry Composition (limits)	
AEROSPACE AND DEFENSE	2.73%
AGRICULTURE	3.00%
BANKING	5.22%
BASIC INDUSTRIES	5.45%
BUSINESS AND CONSUMER SERVICES	13.03%
CHEMICALS AND PLASTIC PRODUCTS	1.92%
CONSTRUCTION	6.46%
CONSUMER PRODUCTS	3.54%
FINANCE, INSURANCE & REAL ESTATE	6.02%
HOTELS AND LEISURE	4.76%
MACHINERY AND EQUIPMENT	4.25%
MEDIA	4.93%
MEDICAL	4.45%
METALS	1.41%
MINING	5.21%
MOTOR VEHICLES AND PARTS	3.56%
OIL AND GAS	5.04%
RETAIL AND WHOLESALE TRADE	6.52%
TECHNOLOGY	4.85%
TRANSPORTATION	4.29%
UTILITIES	3.34%

TTC Grade Composition (limits)	
AAA	0.86%
AA	1.24%
A+	3.09%
A	4.79%
A-	6.37%
BBB+	8.93%
BBB	11.47%
BBB-	13.08%
BB+	11.65%
BB	10.02%
BB-	6.80%
B+	7.30%
B	5.47%
B-	5.20%
CCC+	2.63%
CCC	1.10%

Regional Composition (limits)	
UNITED KINGDOM	21.42%
GERMANY	17.79%
FRANCE	16.29%
SPAIN	15.74%
ITALY	11.95%
NORDICS	10.40%
BENELUX	6.41%

Market Segment	Limit Share	Avg Limit in Millions	Facility Count
LC	66.09%	€50.39	1,991
SME	33.91%	€6.43	8,011

7.0. Appendix III: Deterministic Credit/Climate Scenario Use Case Add-Factor Approach

ZRE also allows for the introduction of discrete (deterministic) innovation shocks determined external to the ZRE models. As examples of applying a deterministic shock scenario use case, we apply shocks in our Z models that are similar to add-factors used in macro-economic forecasting. In Aguais and Forest (2023, e) we developed a short-run climate scenario to 2030 by applying a set of industry sector deterministic shocks as Z 'add-factors' driven by the Real World Climate Scenarios climate 'Meltdown' narrative scenario, see, RWCS (2022) and the University of Exeter (2023). The Z credit factor shocks in this short-run scenario were derived from the published RWCS Meltdown climate narrative and were scaled to the aggregate credit impacts seen in the Great Recession. The RWCS Meltdown scenario was applied to assess however, a different sector mix impact relative to 2007/08.

These shocks may occur in addition to the stochastic ones obtained through the vol-multiplier approach or in isolation as the only shocks affecting the credit-risk factors.

The deterministic Meltdown scenario involves a series of discrete innovations in selected quarters, with no innovations (other than zero) in other quarters (**Figure 13**). These averages reflect shocks of varying magnitudes within sectors **(Table 6**) where we compare the actual shocks observed by industry Z sector in 2007/08 vs the shocks we derive for the meltdown scenario.

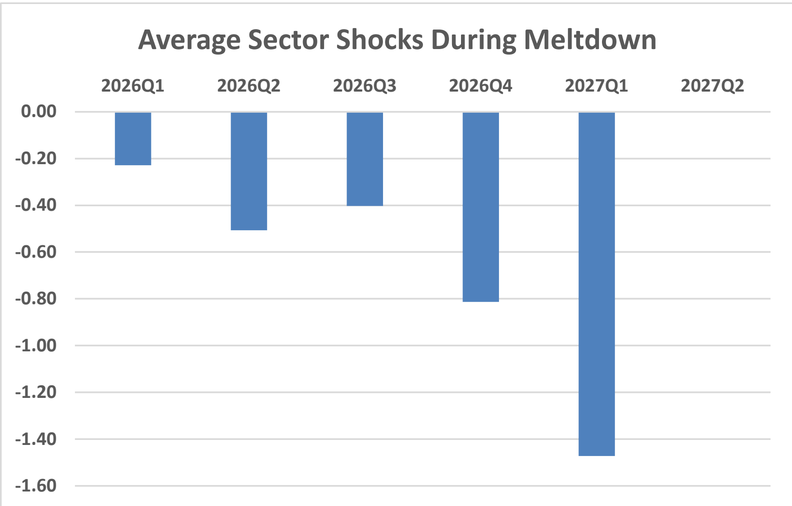

Figure 13: Averages of Sector Shocks in Meltdown Scenario

Source: Moody's EDFs, Z-Risk Engine Calculations and RWCS Meltdown Scenario

Table 6: Cumulative Meltdown Shocks vs Great Recession by Sector

Industry Sector	Great Recession 2007:Q4-2008:Q4	Meltdown' 2026:Q1-2027:Q1
AEROSPACE AND DEFENSE	-3.42	-1.26
AGRICULTURE	-3.68	-2.76
BANKING	-3.80	-4.14
BASIC INDUSTRIES	-4.11	-3.51
BUSINESS AND CONSUMER SERVICES	-3.67	-2.76
CHEMICALS AND PLASTIC PRODUCTS	-3.14	-2.76
CONSTRUCTION	-3.88	-4.77
CONSUMER PRODUCTS	-3.29	-2.64
FINANCE, INSURANCE AND REAL ESTATE	-3.63	-2.76
HOTELS AND LEISURE	-3.83	-4.89
MACHINERY AND EQUIPMENT	-3.17	-3.01
MEDIA	-3.72	-3.01
MEDICAL	-3.21	-2.01
METALS	-3.60	-3.01
MINING	-3.41	-3.01
MOTOR VEHICLES AND PARTS	-2.31	-6.02
OIL AND GAS	-3.31	-5.65
RETAIL AND WHOLESALE TRADE	-2.37	-3.51
TECHNOLOGY	-3.46	-2.01
TRANSPORTATION	-2.91	-4.27
UTILITIES	-3.46	-4.14

Source: Moody's CreditEdge, RWCS and Z-Risk Engine Calculations

We have also run scenarios in which additional shocks occur in 2027:Q3, the quarter after the meltdown (see **Figures 14 and 15**). for the case of an overall average shock with magnitude of 0.5).

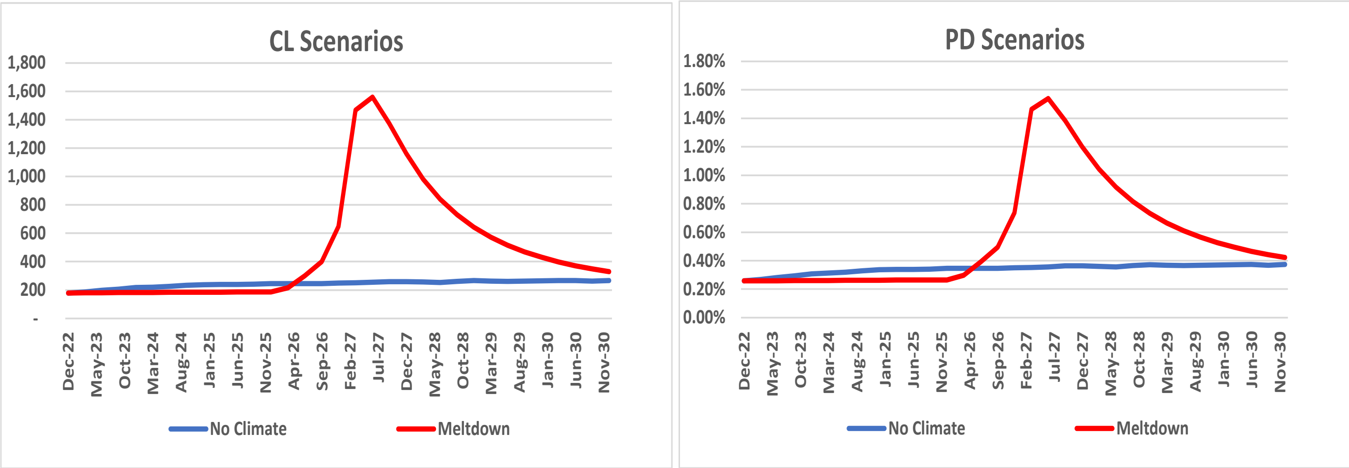

Figure 14: Portfolio Quarterly CLs and One-Quarter-Horizon PDs for Meltdown and No Climate Scenarios

Source: Moody's CreditEdge, RWCS, Z-Risk Engine Calculations

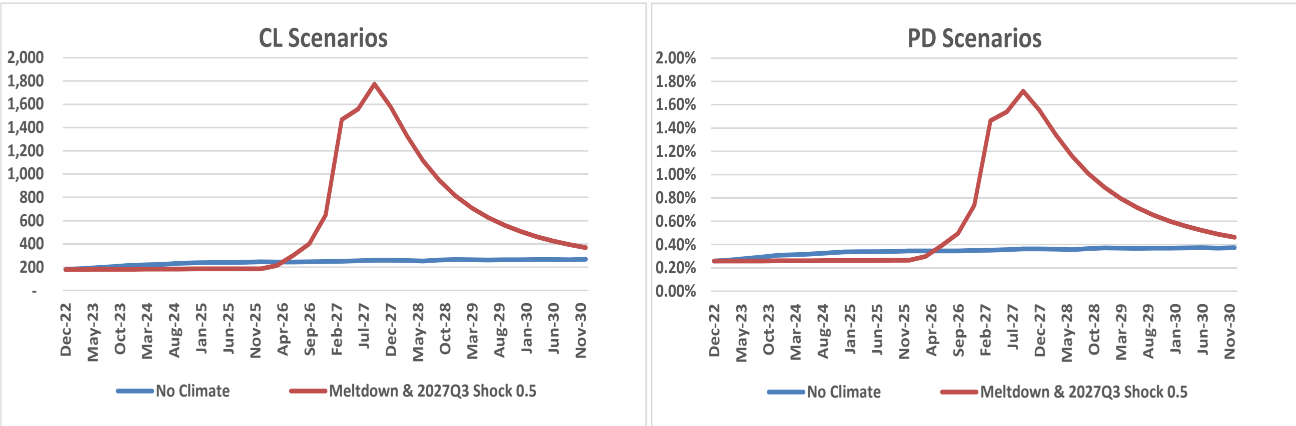

Figure 15: Portfolio Quarterly CLs and One-Quarter-Horizon PDs for Meltdown plus Shock 0.5 and No Climate Scenarios

Source: Moody's CreditEdge, RWCS, Z-Risk Engine Calculations

8.0. Appendix IV: An Example of a Dynamic Net-Zero Climate Strategy Scenario

In climate scenarios, the ECB asks banks to project the portfolio-composition shifts that would predictably occur under each climate scenario over a long (30-year) horizon. With a few exceptions, this will prove challenging for the corporate and commercial portfolios. One could, for example, expect relocations away from coastal areas especially those prone to cyclonic storms; but the optimal response could involve hardening business establishments rather than relocating them. Regarding industry composition, the changes in the main may prove modest, since most shifts from brown to green technologies will likely occur within industries rather than across them.

We see this in auto production, in which a few new entrants have joined the substantial number of legacy firms in producing electric vehicles and all are classified in the motor vehicle industry. In a few cases, however, we can anticipate shifts. For example, oil and gas production seems destined to decline in share, despite efforts by petrol businesses to slow this trend through the development of carbon capture and sequestration (CCS) technologies. And solar and wind sources of electric power will surely gain and nuclear may gain in share as fossil fuel sources decline. However, these composition shifts would largely occur within an amalgamated utility industry.

As another way of managing long-run capital requirements that could be impacted by future climate change, banks could shift the industry and thus the brown versus green composition of its corporate/commercial credit portfolio. As an illustration, we ran the NGFS Net Zero 2050 scenario with a portfolio in which the industry composition remains fixed at its starting 2023 mix and with an alternative portfolio in which the shares of some brown industries fall over 2023-2050 (**Table 7**). These scenarios we present in **Table 7** are outlined to demonstrate ways to use the integrated CRST approach to test different long-run climate scenario options to compare alternative scenario effects.

Table 7 Industry Composition of the Managed Portfolio at the Start and End of the Scenario

Sector	Beta	Limit Shares 2023	Shifted Shares 2050	Change 2023 to 2050
AEROSPACE & DEFENSE	0.76	2.73%	2.73%	0.00%
AGRICULTURE	1.03	3.00%	3.00%	0.00%
BANKING	0.76	5.22%	5.22%	0.00%
BASIC INDUSTRIES	0.89	5.45%	5.45%	0.00%
BUS & CONSUMER SERVICES	0.76	13.03%	14.25%	1.22%
CHEMICALS AND PLASTIC PRODUCTS	0.89	1.92%	1.71%	-0.21%
CONSTRUCTION	1.16	6.46%	6.62%	0.16%
CONSUMER PRODUCTS	0.89	3.54%	4.44%	0.90%
FIN, INSURANCE & REAL ESTATE	0.76	6.02%	5.86%	-0.16%
HOTELS & LEISURE	1.03	4.76%	5.17%	0.41%
MACHINERY & EQUIPMENT	0.76	4.25%	4.00%	-0.25%
MEDIA	0.76	4.93%	5.46%	0.53%
MEDICAL	0.76	4.45%	5.85%	1.40%
METALS	1.42	1.41%	0.88%	-0.53%
MINING	1.42	5.21%	4.22%	-1.00%
MOTOR VEHICLES & PARTS	1.16	3.56%	3.32%	-0.24%
OIL & GAS	1.82	5.04%	1.57%	-3.47%
RETAIL & WHOLESALE TRADE	0.63	6.52%	6.62%	0.10%
TECHNOLOGY	0.76	4.85%	5.89%	1.04%
TRANSPORTATION	1.16	4.29%	4.00%	-0.29%
UTILITIES	1.42	3.34%	3.72%	0.38%

Source: Moody's CreditEdge, Z-Risk Engine Calculations

We show results as affected by two suggested risk management actions over time: drift adjustments, which represent risk control achieved by compelling obligors to maintain their TTC ratings (by deleveraging); and industry-composition shifts (performed by the portfolio manager). As expected, the TTC drift adjustments and the shifts in portfolio composition both reduced the 90th percentile unexpected losses (ULs) (**Figure 16)**. Further, the reductions attributable to each of the two actions were about equal. However, in the Net Zero 2050 scenario, which involves comparatively successful climate-change-mitigation, the magnitudes of the UL reductions are modest, in combination amounting to about five percent. The actions taken reduce only climate-related risks. Since these actions do not address the major share of UL that traces to non-climate shocks, the UL in total reduces by only a minor amount in this illustrative example.

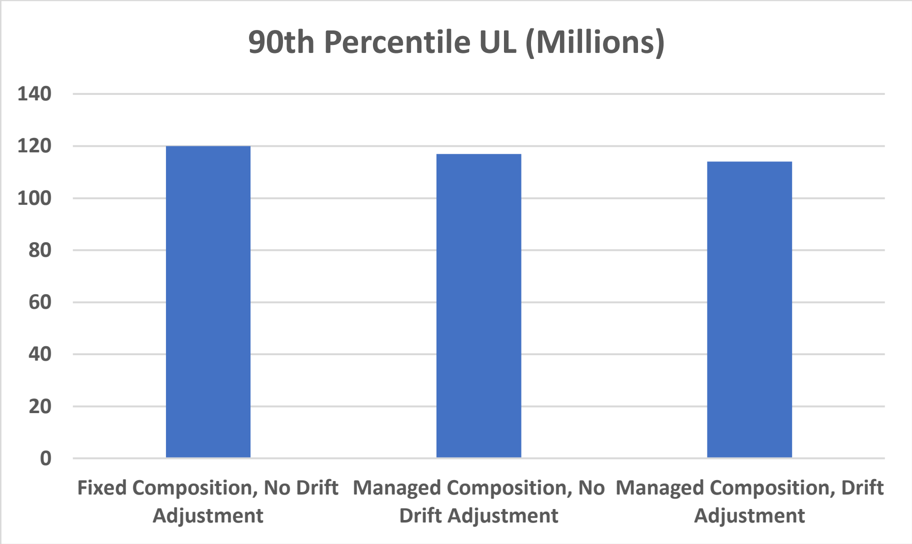

Figure 16: Net Zero 2050 Unexpected Losses in 2050:Q4 Under Various Risk-Management Assumptions

Source: Moody's CreditEdge, Z-Risk Engine Calculations

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