Assessing Climate Related 'Socio-Economic Tipping Point' Risk Impacts by Applying Credit-Factor Shocks[1]

Introduction:

In our Climate Risk Triptych papers (2022), we outlined a framework for climate stress testing ('CST') that involves an empirical, multi credit-factor framework and assumes that climate change would cause the volatility of credit-factor changes to rise. [2] To illustrate this *use case*, we applied illustrative credit factor volatility multipliers based on the GMT projections in various NGFS scenarios and derived estimates of the related, increases in the credit losses for a portfolio representative of US commercial and industrial (C&I) bank loans.

Following the Triptych papers, in our recent 'Hockey Stick' research note (2023) we provided regression analysis to demonstrate the relationship between GMT and rising atmospheric CO2 concentration. We also demonstrated that the data up to the present time don't indicate a statistically significant relationship between global warming as gauged by GMT and broad economic risks (volatility) as measured by either the CCAR Vol Index or an aggregate index of credit cycle shocks.

In this Climate Research Note, we develop a second use case for developing CST scenarios. Here we apply future, narrow, 'shocks' representing socio-economic tipping points ('SETP') to assess credit losses through credit factor simulations to 2050.[3] To develop CST scenarios, we have introduced climate effects into ZRE's, credit-risk models so far through these two separate use cases:

- **Parametric approach (volatility):** assumes that the volatilities of credit-risk factors rise as GMT increases and climate-related, credit events occur with growing frequency and magnitude, and,
- **Event approach ('shocks'):** assumes that at particular future time points large credit shocks related to climate change occur.

In both *use cases*, climate events of all types including sudden escalations in costs of physical damage, brown-to-green transition, and asset stranding could cause potential climate-related, credit effects. This framework provides a tractable way to develop climate change credit scenarios. Since we're modelling climate impacts on company credit risk, we view all of the events both climate and non-climate as affecting current

1 For this ZRE Climate Research Note, all feedback and comments welcome, any errors or omissions remain the responsibility of the authors.

2 See Aguais and Forest, 2022, a, b and c, and; *'Climate-Change Scenarios Require Volatility Effects to Imply Substantial Credit Losses – Shocks Drive Credit Risk Not Changes in Economic Trends'*, in: ***Decision Making for the Net Zero Transformation: A Compendium of Best Practice***, www.frontiersin.org.

3 See Kees et al, 2022, for an example of applying the concept of climate 'SETPs' on a microregional basis for a housing market subject to climate-driven sea-level rises. This micro-application contrasts with our application of 'SETP' shocks applied here on a global basis across industry sector and regional factor dimensions. In general, SETP shocks should be considered as narrower than the broader longer-run climate-driven 'tipping points' generally considered in the literature.

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and expected-future, cash flows and cash-flow volatilities. These climate risk *use cases* can be assessed on a standalone basis (increasing volatility or discrete shocks) or in combination as we also present below.

In much of the recent focus on developing CST assessments, the usual approach has been applying top-down IAM derived scenarios like those from the NGFS directly with company level credit risk models (bottom-up). These approaches have so far, generally suggested limited impacts of climate on credit risk, partly due to the mostly absent application of unexpected shocks.

Alternatively, our recent climate research emphasizes the need to apply a multiple credit-factor approach involving market-based measures of risk. We then add to this approach climate-related credit shocks of assumed magnitudes and frequencies.

The CST use cases in this research note are organized as follows, where we:

- Provide a short overview for *integrated CST scenario development* (**Section 1**),
- Briefly review the climate 'tipping point' literature, which focuses on broader, complex physical tipping points compared to our focus here on narrow *financial and* SETPs, (**Section 2**)
- Summarise past, *observed negative financial Z credit cycle shocks* by industry sector and region to inform the magnitude of the initial shock 'proxies' we apply, (**Section 3**)
- Analyse *climate risk impacts* by applying these proxy SETP shocks,(**Section 4**), as we:
  - Apply SETP 'shocks' on a standalone basis in the year 2035, and incorporate cross-sector relative carbon impacts using illustrative *'climate carbon intensity betas'*, and
  - Assess climate credit risk impacts using combinations of the two use cases, by, applying a GMT volatility multiplier derived from the NGFS Net Zero GMT scenario, in conjunction with an SETP shock in 2035.

The approach applied in this research note is consistent with the Climate Triptych papers where we ran various Z-Risk Engine climate-driven credit factor risk simulations to 2050. Therefore, to illustrate relative sector impacts of the SETP shocks we utilise the simplified credit portfolio characteristics from the Triptych papers. In addition, to illustrate the combined volatility and shocks *uses cases* we also introduce an expanded credit portfolio (See **Appendix**) of roughly £43 billion with about 2k facilities. This broader portfolio includes the standard ZRE industry sectors but is expanded to include both the NA and UK regions. This more elaborate credit portfolio allows us to develop these CST impacts by applying a credit portfolio that is more similar to what a bank would actually have for its large-corporate and SME counter-parties and exposures.

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1. Brief Overview: An Integrated Approach to Climate Stress Testing Scenario Development:

The climate risk *use cases* presented here using the ZRE credit-factor model take account of the general industry discussion points related to CST research we highlighted in the Triptych papers to improve the application of CST scenarios, namely that:

- *Volatility measures and systematic unexpected economic shocks* drive potential climate risks, which are generally lacking in current CST approaches,
- CST scenarios require the inclusion of a broader range of future climate change outcomes, including, more *extreme near-catastrophic future 'states of the world'*,
- Detailed, dedicated *industry and region systematic credit-factor models*, improve substantially on 'top-down' approaches which rely too much on bridging from macro variables to company-level models, leaving out key industry/region drivers of credit risk, and,
- Observed market-based systematic credit cycle models provide a *stronger empirical foundation* for CST scenario development generally.

The climate CST *use cases* we develop are designed to support these overall enhancements in the application of climate risk scenarios generally.

This solid credit-factor empirical approach is flexible, is complementary to other CST approaches and can potentially be integrated with a range of top-down scenarios. Additional satellite models can also provide richer 'drivers' for the factor model, including detailed emissions measures and more elaborate carbon intensity models, carbon mitigation policies, physical risk impacts and future energy market evolution.

Applying a robust, empirical credit factor model also provides a *better approach than seeking to project company-specific financial data over very long horizons*.

2. Broader Climate 'Tipping Points' vs 'SETP' Risk Shocks:

An interesting and substantial discussion point in climate research generally, has focused on what are referred to broadly as climate 'tipping points' ('TP'). Climate change is a quite complicated global environmental dynamic, therefore much of climate research has focused on complex physical manifestations of excess atmospheric carbon and its diverse environmental impact and link to observed changes in GMT. Rising global sea-levels from melting glaciers, de-forestation driven by industrialisation and changing complex weather and ocean patterns are all part of the planet's complex climate evolution.

Climate 'tipping points' have been described as 'cascading, non-linear' processes with the potential for some aspects to be *irreversible*. While the underlying complex physical processes are more long-dated, the culminating TP impact can manifest in multiple ways as more discreet events or focused 'step change' processes measured over shorter time horizons. Modelling supposed non-linear climate change processes generally, is an extremely challenging effort.

This research note is focused on applying climate change TP logic as more, narrow SETP shocks. For the broader climate TP literature, see, Franzke et al, (2022), Wunderling et al., (2022), Lenton et al., (2013, 2019), Keen et al., (2021, 2022), and Chavas et al., (2016). Climate TPs more broadly are also discussed throughout much of the most recent IPCC AR6 Synthesis Report, Lee et al., (2023).

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In contrast to the focus on complex physical climate processes, assessing the economic or financial impact of climate SETPs is even less developed. As Dietz et al. (2021) point out; '*Climate tipping points are subject to considerable scientific uncertainty in relation to their size, probability, and how they interact with each other……Their economic impacts are even more uncertain.*' [4] Dietz et al. (2021) find that, 'climate tipping points increase global economic risk….[as] they increase economic losses nearly everywhere.' [5]

Over the last roughly 30 years we observe a few financial and economic risk 'shocks', e.g., 2008/09. While these observed 'shocks' are not directly related to climate change as our Hockey Stick note suggested, they do provide an empirical starting point for developing and adapting these financial 'shocks' as proxies to support the concept of climate SETPs. The development of detailed climate narratives combined with adapting and applying shocks in climate credit risk simulations then forms the basis for the 'event driven' climate scenario *use case* presented here.

3. Developing Illustrative Economic Credit Factor Shocks to Assess Climate SETPs:

A. Overview:

In this section we:

- Assess past unexpected credit risk 'shocks' (represented by observed Z MM model errors) for 1990-2022 using the ZRE approach estimated from the full history of Moody's CreditEdge EDFs, and,
- Provide estimates of the *average and maximum negative credit cycle shocks* observed across the standard ZRE industry sector and region Z credit factor segmentation.

Our objective is to propose these observed *average and maximum* negative shocks as preliminary estimates we can apply in our CST credit risk simulations to illustrate the application of climate SETP shocks, presented in the following **Section 4**.

B. Historical Credit Factor Shocks By Industry and Region Z: 1990-2022:

In ZRE each Z industry and region credit factor is modelled as a second-order auto-regressive ('AR') process representing a combination of mean-reversion and momentum ('MM'). These Zs represent stationary processes each with a unit variance. **Figure 1** below shows the aggregate (industry and regions combined) Z MM credit cycle index values in standard deviation units with positive Z ('good economic conditions') and negative Z observations ('bad economic conditions').[6] **Figure 2** then shows the aggregate Z MM credit cycle index model errors.

4 See Dietz, S. et al., (2021), page 1.

5 See, Dietz 2021, page 1.

6 As in the 'Hockey Stick' research note, the aggregate Z MM model errors derive from individual industry and region Zs aggregated using equal weights.

Figure 1: Monthly Average Sector-Z Index Values, 1990-2022
(Standard deviation of past, monthly, annual changes in Zs)
Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

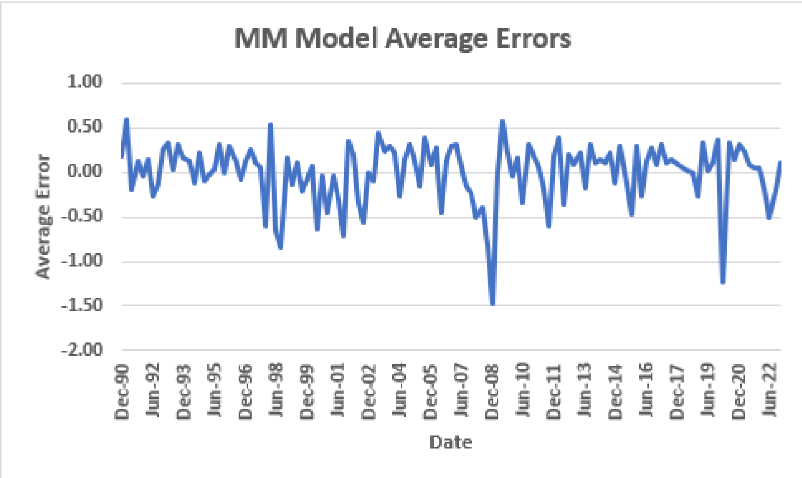

Figure 2: Quarterly Averages of Sector-MM Model Errors, 1990-2022
(Standard deviation of past, monthly, annual changes in Zs)
Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

In **Figure 2**, we clearly see the impacts of the 2008-09 'Great Recession' and the Covid Pandemic of 2020 which are exhibited as large negative shocks with the largest shock equal to **-1.46 sigma**. The average negative shock observed in **Figure 2** is **-.38 sigma**.

C. Obsereved Historical Credit Factor Shocks By Industry and Region Z: 1990-2022:

ZRE develops future PIT credit risk assessments by applying a multi credit-factor approach applied using industry sector and regions. For a large global bank, the industry sectors and region factors are customised to represent a bank's specific portfolio. The region factors we develop from Moody's CreditEdge EDF histories can be developed for disaggregated individual countries or for broader regions such as Europe etc. While these factor segmentations are customised in implementation, for research presentation we use a standard segmentation of 21 industries and 12 regions split Corp/FI.

Using this standard segmentation and focusing on individual industry and region Zs, **Table 1** lists the largest observed negative systematic credit shocks as measured by ZRE for each of the standard industry and region sectors.

Given that the 2008-09 period is dominated by financial influences, FIs and discretionary consumption like Hotels and Leisure exhibit the largest MM model errors or 'shocks', with less cyclical industries lower in the table. As we see in **Figure 2**, the 2008/09 'great recession' exhibited the largest cyclical shock so in **Table 3** below, the largest negative shocks are derived primarily from this period. We also see that the observed credit-factor shocks vary a fair amount across different sectors and regions.

SECTOR	MAX NEG ERROR
HOTELS AND LEISURE	-2.24
FINANCE, INSURANCE AND REAL ESTATE	-2.19
PACIFIC CORPS	-2.19
NORTH AMERICA FI	-2.13
PACIFIC FI	-2.12
ASIA FI	-2.11
EUROPE FI	-2.10
NORTH AMERICA CORPS	-2.02
OIL AND GAS	-1.92
LATIN AMERICA FI	-1.90
BANKING	-1.83
UK FI	-1.79
MINING	-1.78
LATIN AMERICS CORPS	-1.75
UK CORPS	-1.69
AEROSPACE AND DEFENSE	-1.66
ASIA CORPS	-1.63
EUROPE CORPS	-1.57
NORDIC FI	-1.55
RETAIL AND WHOLESALE TRADE	-1.54
CHEMICALS AND PLASTIC PRODUCTS	-1.53
AGRICULTURE	-1.49
MOTOR VEHICLES AND PARTS	-1.46
TRANSPORTATION	-1.43
NORDIC CORPS	-1.43
MEDICAL	-1.40
BASIC INDUSTRIES	-1.38
BUSINESS AND CONSUMER SERVICES	-1.34
CONSUMER PRODUCTS	-1.34
MEDIA	-1.32
TECHNOLOGY	-1.32
UTILITIES	-1.32
CONSTRUCTION	-1.31
MACHINERY AND EQUIPMENT	-1.27
METALS	-1.22

Table 1: Largest Negative MM Model Errors by Industry/Region: 1990-2022 (Standard deviation of past, monthly, annual changes in Zs)
Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

In the following application of Z shocks within the future climate credit loss simulations, to be clear these should be considered as proxies for potential future SETP shocks. The historical Z shocks are shown for reference primarily as these are not on a historical basis, related directly to climate as the Hockey Stick note suggested empirically. They do provide a broad reference starting point for applying a climate shock *use case* to develop future climate scenarios. In a CST implementation we would expect that a combination of observed historical shocks, more detailed climate narratives and a structured benchmarking process would inform how climate shocks are applied. In using historical estimates now as guidelines in scaling the climate shocks in our illustrative scenarios, we're implicitly assuming that future climate shocks will have impacts similar to past non-climate ones. Therefore, these examples remain illustrative for now.

To illustrate the application of the ZRE climate shock *use case* in the following section we apply both average Z shocks using the same negative **0.5** sigma to all industries and region Zs representing roughly the average observed, negative historical shock. We also apply an average negative maximum **1.5** sigma shock across all industries and regions as a more extreme proxy.

4. Developing Climate Stress Test Credit Losses to 2050 by Applying Proxy Credit Factor Shocks and Carbon Intensity Betas:

A. Overview:

The discrete shocks in our illustrative scenarios enter as additive increments to the randomly drawn, innovation (or error) terms that drive the Monte Carlo Z credit-factor simulations. Thus, if for a sector ***s*** the randomly drawn innovations in quarter ***q*** have the values ***u(i, q)*** where ***i*** indexes simulations and the discrete shock in that quarter for the sector has the value ***s(q)***, then the innovations driving the Z sims for that sector in that quarter will have the values ***u(I, q) + s(q)***.

In the two illustrations below, we apply discrete shocks of average magnitudes of **-0.5** and **-1.5** respectively in the first quarter of 2035. We then distribute those average shocks to individual sectors by applying sector 'carbon intensity betas' to the average shock. This allows sectors with greater climate exposure to combined physical and carbon adaptation risks to experience larger shock impacts than sectors with lesser climate exposure.

The development and application of differential carbon intensities, usually derived from observed CO2 emissions data sources across industry sectors is a key component of the evolving CST research. This literature generally differentiates carbon-intensive sectors from low or zero carbon sectors because carbon mitigation is suggested as one of the key future drivers of climate risk either through the stranding of carbon energy sources (fossil fuels) or the application of aggressive, abrupt carbon mitigation policies.

Briefly, examples of the application of 'climate or carbon betas' is found in assessments of climate impacts on financial assets, see Huij et al., (2023), and Chini and Rubin (2022), and also in broader IAM-style models assessing the future social cost of carbon, for example see, Dietz et al., (2018). A key paper assessing climate stress test impacts on the Dutch banking sector by Vermeulen et al., (2021) develops a 'transition vulnerability factor (TVF) [that] can be thought of as the factor loading in a standard asset pricing model.[7]

For the analysis of applying shocks here in conjunction with simplified carbon intensity betas, we've set the values of the illustrative carbon intensity betas to rise together, but not in full proportion, to the carbon intensity of the different sectors as revealed

7 See Vermeulen, 2021, page 4. The TVFs applied in this paper are, 'scaling factors [based] on the embodied emissions of the final good and services in each industry.', also page 4.

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in a variety of sources including Walther (2023).[8] However, since most view the carbon intensities as related primarily to transition risk and less so physical risk and inasmuch as our shocks reflect all climate-related risks combined, we've scaled the betas so the variation across sectors is smaller than the variations in carbon intensities. So far since the empirical evidence for credit impacts of climate change is missing, much less evidence of sectoral variations in impacts, we really have limited guidance for scaling these illustrative betas. Thus, one may view the carbon intensity betas in **Table 2** below as plausible placeholders awaiting replacement by potentially empirically derived estimates. To apply these carbon intensity betas with the assumed shocks we present below, we simplify the regional segmentation by aggregating the NA and UK FI/Corps regions as shown in **Table 2**.

Sector	Beta
All Average	1.00
AEROSPACE AND DEFENSE	0.76
AGRICULTURE	1.03
BANKING	0.76
BASIC INDUSTRIES	0.89
BUSINESS AND CONSUMER SERVICES	0.76
CHEMICALS AND PLASTIC PRODUCTS	0.89
CONSTRUCTION	1.16
CONSUMER PRODUCTS	0.89
FINANCE, INSURANCE AND REAL ESTATE	0.76
HOTELS AND LEISURE	1.03
MACHINERY AND EQUIPMENT	0.76
MEDIA	0.76
MEDICAL	0.76
METALS	1.42
MINING	1.42
MOTOR VEHICLES AND PARTS	1.16
OIL AND GAS	1.82
RETAIL AND WHOLESALE TRADE	0.63
TECHNOLOGY	0.76
TRANSPORTATION	1.16
UTILITIES	1.42
CORP REGION	1.02
FI REGION	0.76

Table 2: Assumed, Illustrative 'Climate Carbon Intensity Betas'
Source: Moody's CreditEdge EDFs, Z-Risk Engine standard industry segmentation, NA and UK regions are aggregated to Corps/FIs to simplify and Walther (2023), Table at bottom of page 3.

8 We should be clear that these illustrative carbon betas are not directly derived from emissions data but are based indirectly on the Walther (2023), 'Table: Carbon-intensive sectors: transition risk varies greatly', found on page 3. Overall, the magnitudes of 'carbon and climate betas' found across the literature varies substantially and for the most part makes simplifying assumptions such as 'technology change is fixed', which is a quite unrealistic assumption usually applied using fixed-coefficient I/O models. It's also true that the largest 'TVF' betas applied by Vermeulen et al., are quite a bit larger than the illustrative examples we apply here.

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B. Applying CST Shocks Utilizing Historical Credit Factor Shocks:

Here we apply two different proxy shocks to broadly suggest the impact of potential future shocks driven by various SETPs (WWIII?), sudden asset stranding, or abrupt changes in carbon mitigation or a combination of various SETP drivers. To assess individual industry sector impacts of shocks combined with climate betas, we apply the simplified credit portfolio characteristics developed in the Climate Triptych Papers.

See below in **Figures 3-6**, the estimates of 2035, mean and 95th percentile loss rates (loss/limit) from Z sims that include discrete climate shocks in 2035Q1 of average magnitudes of **-0.5** and maximum magnitude of **-1.5** (sigma) respectively. These are coupled with the carbon intensity betas from **Table 2**. Other than these discrete SETP proxy shocks and climate carbon betas, the scenarios involve only the standardized credit risk impacts contained in ZRE credit-factor loss simulations. The impacts shown on industry sectors for the combined shocks and betas is contrasted to the blue bars representing 'no-shock' impacts. As can be seen in **Figure 6**, the oil and gas sector with the highest carbon beta combined with the 1.5 sigma shock example sees loss rates rise from a 'no-shock' average loss rate of about 70 bp to about 20%!

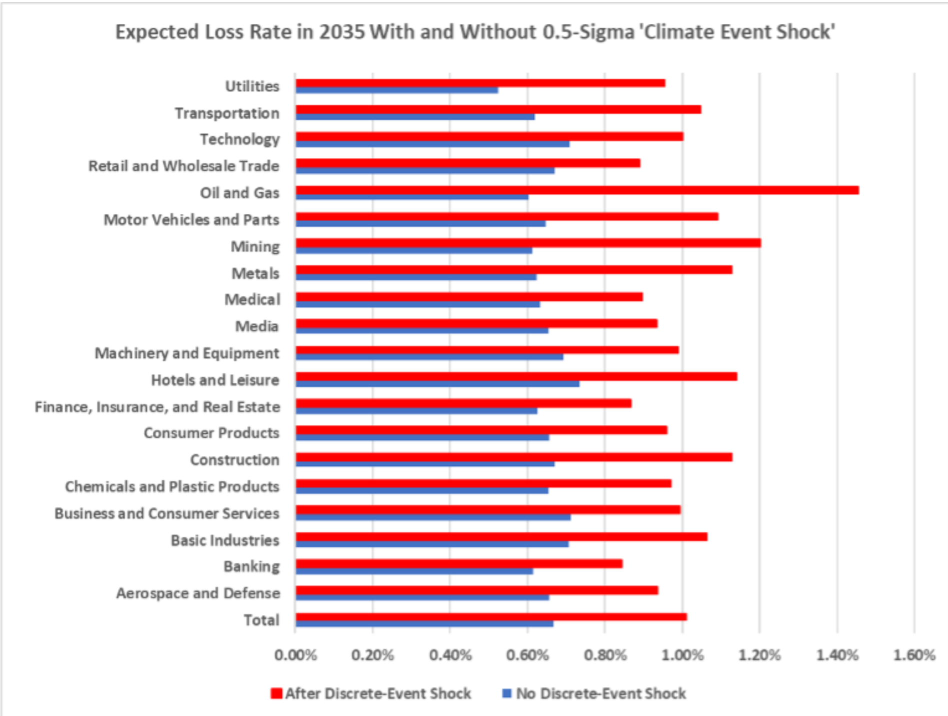

Figure 3: 'Climate Event Shock' Applied in 2035 (0.5 Sigma) (Expected % Credit Loss Rate)
Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

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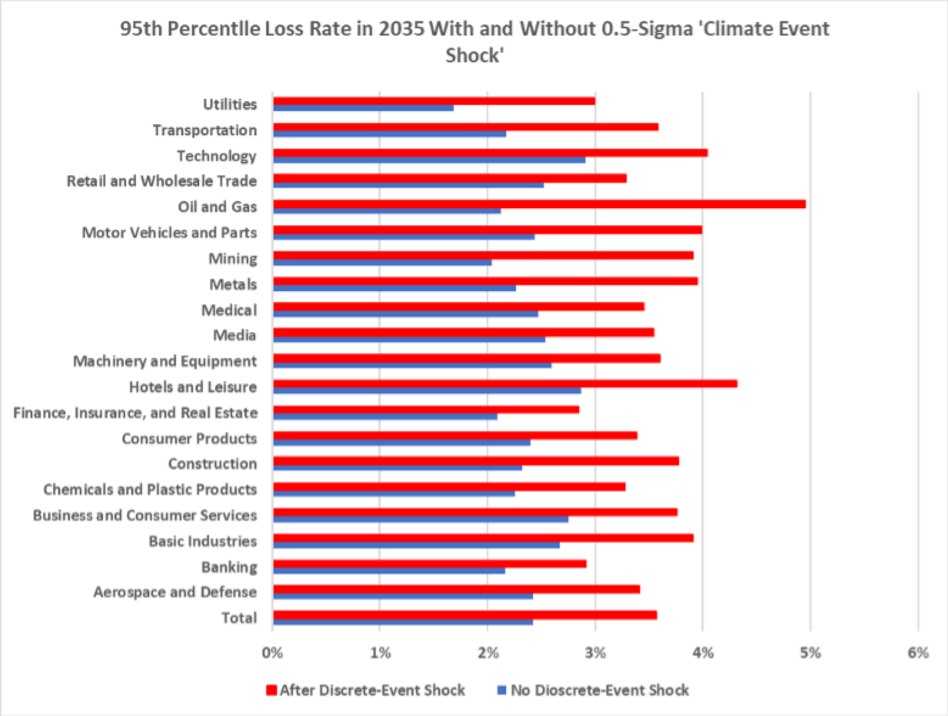

Figure 4: 'Climate Event Shock' Applied in 2035 (0.5 Sigma) (95th Percentile Credit Loss Rate)
Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

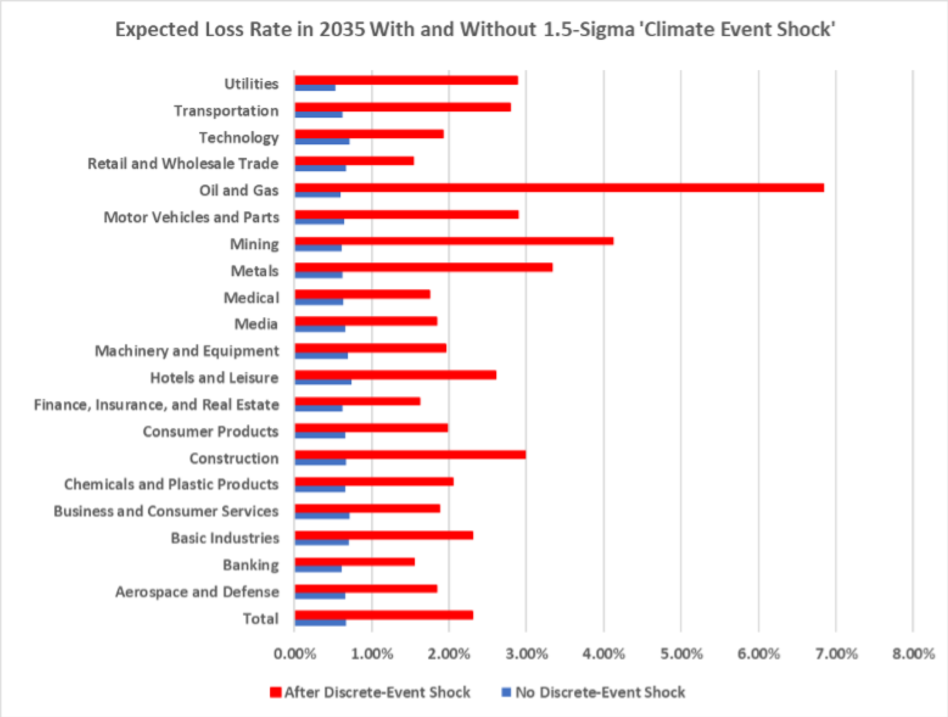

Figure 5: 'Climate Event Shock' Applied in 2035 (1.5 Sigma) (Expected % Credit Loss Rate)
Source: Moody's CreditEdge EDF sand Z-Risk Engine calculations.

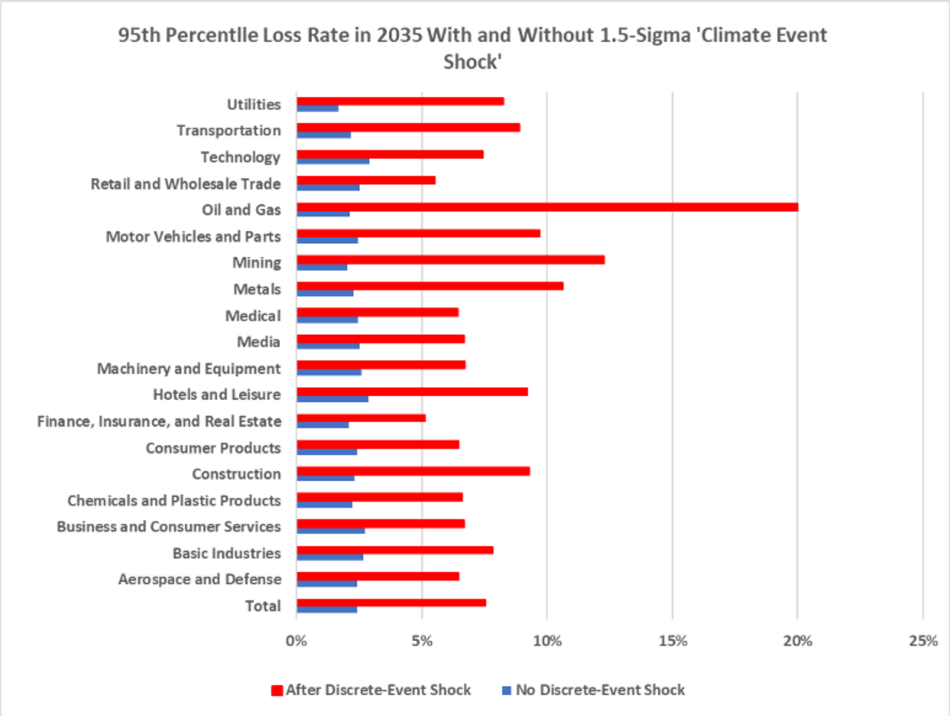

Figure 6: 'Climate Event Shock' Applied in 2035 (1.5 Sigma) (95th Percentile Credit Loss Rate)

Source: Moody's CreditEdge EDFs and Z-Risk Engine calculations.

These industry and total credit risk simulation results apply the same portfolio characteristics we utilised in the Climate Triptych papers with industry composition and TTC risk similar to the US bank, commercial-and-industrial (C&I) loan portfolio. Due to the portfolio's characteristics, we can get meaningful loss estimates for individual industries because the total portfolio (as outlined in the Triptych appendices) distributes the industry composition shares downward.[9] We see in the Figures those industries with comparatively large, climate betas (e.g., oil and gas, mining and utilities) have larger loss rates than industries with smaller, climate betas (e.g., banking).

Note: in these illustrations that apply SETP shocks, we apply the same average and maximum observed, negative shocks as proxies from our MM model to all industries and regions – this is for illustration purposes. In an implementation of this proposed CST approach, the shocks applied like the volatility multipliers could of course vary by industry sector and region. In addition, we can think of growing future low or zero-carbon sectors as benefiting from large 'green' technology improvements and potentially having lower not higher shocks or volatility add-ons.

9 Alternatively, in the following **Section 5**, for the combined use cases for shocks and volatility, we use a more realistic portfolio as outlined in the **Appendix** with roughly 2k credit facilities of varying kinds, and a full risk grade scale mapped to Agency Rating grades. While this portfolio in the **Appendix** and applied in **Section 5** is more realistic, it is still small enough that it is hard to break out industry-specific losses, which are shown in **Section 4**, alternatively using the portfolio approach applied in the Triptych papers.

5. Developing Climate Credit Factor Shocks in Conjunction with Climate GMT Driven Volatility:

The next results below combine a climate scenario implemented parametrically (volatility multiplier) with a climate-related discrete shock of magnitude **-1.0** in 2035:Q1. The parametric sims assume that the volatility of quarterly innovations rise with the GMT trends assumed in the **NGFS Net Zero 2050** scenario (see Triptych paper for more explanation). We show first in **Figure 7**, expected credit losses for just the NGFS Net Zero scenario, with the blue line representing no increase in volatility due to rising GMT and the red line representing application of the scaled GMT multiplier.

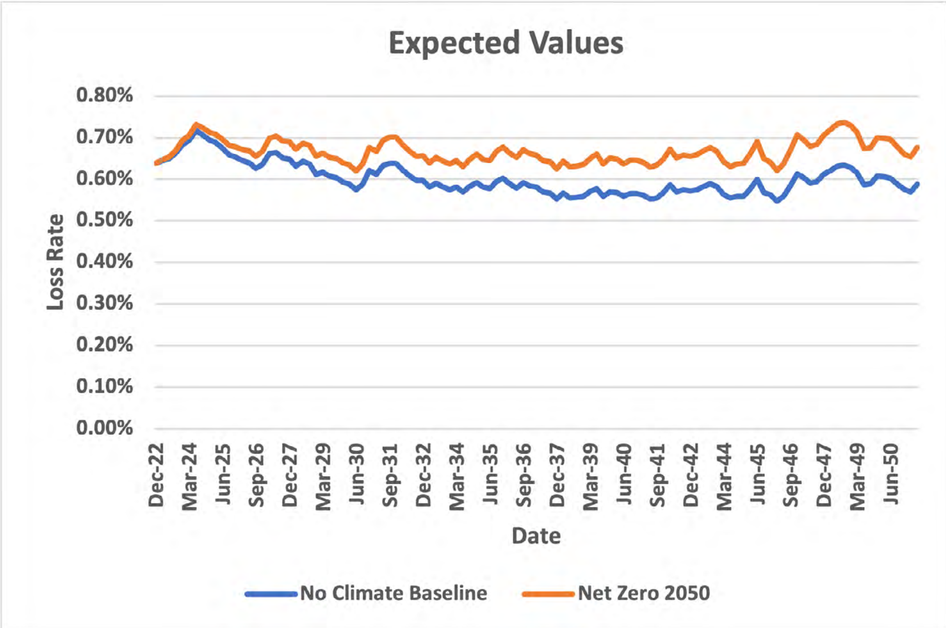

Figure 7: NGFS Net Zero Scenario – to 2050
(Expected % Credit Loss Rate)
Data Sources: *Moody's CreditEdge EDFs*, Z-Risk Engine Calculations and NGFS, 1662723618051-V3.2%20NGFS%20Phase%203.zip.

In **Figure 8**, as we see below, as the **1.0** sigma shock is applied in 2035 across-the-board, it creates a major surge in the aggregate, expected, annualized loss rate in 2035:Q1 and in subsequent quarters with the loss rate converging over time to the values attributable only to credit risk driven characteristics of the simulation. It is helpful to point out that the persistence of the shock after 2035 for a number of years relates to the persistence effects in the momentum component of the ZRE MM model.

The NGFS Net Zero 2050 scenario loss rates remain above those in which climate change has no effects, but the discrete shock adds considerably to the losses attributable to the NGFS Net Zero GMT rise scenario on its own. The overall time horizon presented in these simulation time series of simulated, annualized loss rates starts in 2023:Q1 and extends up to 2051:Q2.

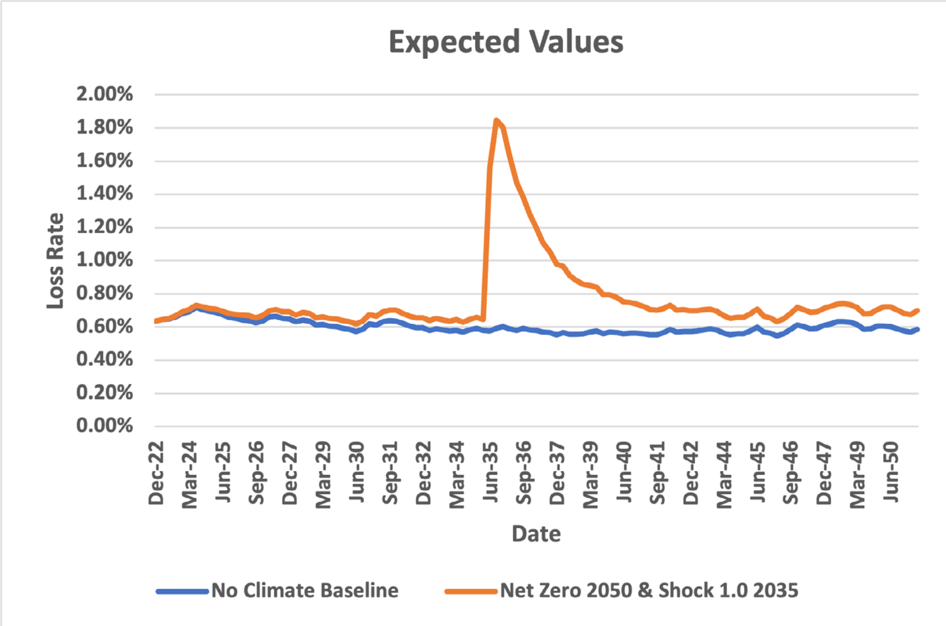

Figure 8: 'Climate Event Shock' Applied in 2035 (1.0 Sigma) (Expected % Credit Loss Rate)
Data Sources: *Moody's CreditEdge EDFs*, Z-Risk Engine Calculations and NGFS, 1662723618051-V3.2%20NGFS%20Phase%203.zip.

In assessing the 95th percentile combined **1.0** shock, and carbon beta, coupled with the NGFS Net Zero volatility factor shown in **Figure 9** below, we see that this tail loss scenario rises rapidly in the early part of the simulation interval due to correctly modelled monotonic increases in the overall variance.[10] The GMT volatility multiplier is also applied throughout the horizon and then we see clear persistence effects from the credit cycle momentum variable after the shock is applied in 2035.

10 As we point out in Forest and Aguais (2019) this rising variance correctly represents rising risk across time in contrast to short-run regulatory driven capital stress test scenarios with substantial recession risk in the first year and then declining variance of risks across time after that. We refer to this risk measurement concern with how short-run stress tests are specified as 'variance compression bias'.

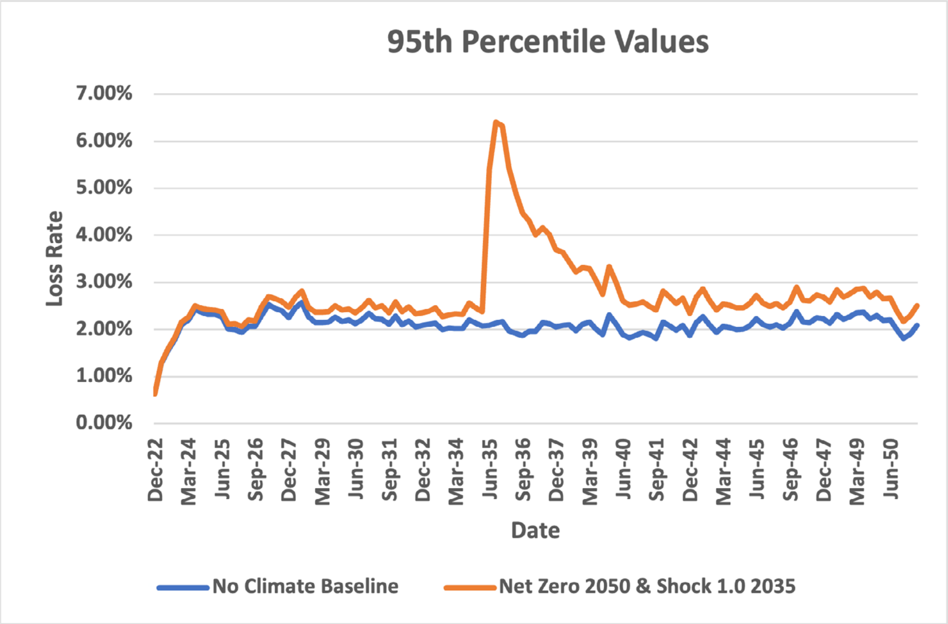

Figure 9: 'Climate Event Shock' Applied in 2035 (1.0 Sigma) (95th Percentile Credit Loss Rate)
Data Sources: *Moody's CreditEdge EDFs*, Z-Risk Engine Calculations and NGFS, 1662723618051-V3.2%20NGFS%20Phase%203.zip.

As explained above, these scenarios involve a portfolio different from the C&I one used in **Section 4**. Here we apply a portfolio of 2,018 facilities outlined in the **Appendix** that includes a mixture of North American and UK exposures across several industries and a broad risk grade scale. The facility count of 2,018 is too small for producing stable industry results, however, so we show only loss rates for the total portfolio as in **Figures 7-9**.

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Summary:

In this Climate Research Note, we outline a second climate stress test *use case* designed to enhance the capability to develop flexible, more realistic long-run climate risk scenarios. This *use case* applies the event driven logic of unexpected future shocks that represent potential socio-economic tipping points. We apply discreet future shocks in an empirical credit-factor model at a future time point, specifically in 2035, in conjunction with increases in future volatility.

To provide some preliminary empirical proxies for applying future shocks we assess past observed model errors derived from our ZRE multi credit-factor MM model approach that were observed from 1990-2022. Specifically, the empirical shocks represent the MM model residuals or model errors in a global segmentation of industry sectors and regions estimated from roughly 37k market-based EDFs. *The shocks we apply are illustrative but also are founded in past credit-driven shocks, therefore they represent starting proxies for what might happen in the future in relation to complex climate influences.*

Consistent with much of the climate stress test literature focused on the impacts of migration from a high-carbon to low-carbon economy, we also apply a set of simplified carbon intensity betas. *These betas are illustrative but are nominally related to observed CO2 emissions data.*

Climate stress testing is currently receiving substantial regulatory attention and to-date much of the climate risk research has not applied dedicated, empirically-based credit-factor models to enhance the ability to develop scenarios stemming from future risks. The approach we outline provides a richer foundation for assessing credit risk impacts – because it incorporates detailed systematic credit risk drivers. ***Seeking to model complex climate impacts on credit risk requires more complex credit risk models.*** The two *use cases* we apply for volatility and shocks provides a flexible framework for developing future climate risk scenarios, whose risk impacts have generally not yet been observed.

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Bibliography:

Aguais, S. and Forest, L. 2022 a, 'Climate Change Credit Risk Triptych, Paper One: Smooth NGFS Climate Scenarios Imply Minimal Impacts on Corporate Credit Losses', www.z-riskengine.com, November.

Aguais, S. and Forest, L. 2022 b, 'Climate Change Credit Risk Triptych Paper Two: Climate Change Volatility Effects Imply Higher Credit Losses', www.z-riskengine.com, November.

Aguais, S. and Forest, L. 2022 c , 'Climate Change Credit Risk Triptych Paper Three: Climate Change Macro Volatility Effects Imply Higher Credit Losses', www.z-riskengine.com, November.

Aguais, S. and Forest, L. 2023, 'The Climate Change 'Hockey Stick' is Observable – But Climate Change Impacts on Economic Risks are Note Yet Observable', Z-Risk Engine, Climate Stress Testing Research Note Num One, March.

Chavas, J-P., C. Grainger and N. Hudson, 2016, 'How should economists model climate? Tipping points and non-linear dynamics of carbon dioxide concentrations', Journal of Economic Behaviour & Organisation, 132, 56-65, February.

Chini, E. and M. Rubin, 2022, 'Time-varying Environmental betas and Latent Green Factors', Lancaster University Working Paper, July.

Dietz, S., C. Gollier and L. Kessler, 2018, 'The climate beta', Journal of Environmental Economics and Management, 87, 258-274.

Dietz, S., 2021, 'Economic impacts of tipping points in the climate system', Proceedings of the National Academy of Sciences, Vol. 118 no 34.

Franzke, C. L. E. et al., 2022, 'Perspectives on tipping points in integrated models of the natural and human Earth system: cascading effects and telecoupling', Environmental Research Letters, 17, January.

Forest, Lawrence and S. Aguais, 2019, 'Variance Compression Bias in Expected Credit Loss Estimates Derived from Stress-Test Macroeconomic Scenarios', Z-Risk Engine Case Study Research Paper, ZRE web site, April.

Huij, J. et al., 2023, 'Carbon Beta: A Market-Based Measure of Climate Transition Risk Exposure', SSRN, https://dx.doi.org/10.2139/ssrn.3957900.

Kees, CH van Ginkel, M. Haasnoot and WJ Wouter Botzen, 2022, 'A stepwise approach for identifying climate change induced socio-economic tipping points', Climate Risk Management Volume 37, 2022, 100445

Keen, S. et al., 2021, 'Economists' erroneous estimates of damages from climate change', Proceedings A, The Royal Society, August, arXiv:2108.07847.

Keen, S. et al., 2022, 'Estimates of economic and environmental damages from tipping points cannot be reconciled with the scientific literature', PNAS 2022 Vol. 119 No. 21 e2117308119.

Lee, H. et al, 2023, 'AR6 Synthesis Report: Climate Change 2023', Intergovernmental Panel on Climate Change, March.

Lenton, T. et al., 2019, 'Climate tipping points — too risky to bet against', The growing threat of abrupt and irreversible climate changes must compel political and economic action on emissions', Nature, November.

Lenton, T. and JC. Ciscar, 2013, 'Integrating tipping points into climate impact assessments. Climate Change 117, 585–597.

Moody's Analytics 2016, CreditEdge: 'A Powerful Approach to Measuring Credit Risk, Brochure'. https://www.moodysanalytics.com/-/media/products/CreditEdge-Brochure.pdf.

Network for Greening the Financial System, 2022, 'NGFS Scenarios for central banks and supervisors', www.ngfs.net, September.

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., Jansen, D. J., and Heeringa, W. (2021), 'The heat is on: a framework for measuring financial stress under disruptive transition scenarios', Ecol. Econ. 190, 107205. doi: 10.1016/j.ecolecon.2021.107205

Walther, U., 2023, 'Climate Stress Tests – Are banks fit for the green transition?', Deutsche Bank EU Monitor, Global financial markets, January.

Wunderling, N. et al, 2022, 'Global warming overshoots increase risks of climate tipping cascades in a network model, Nature Climate Change, December.

Appendix – Illustrative Credit Portfolio Used in Section 5 When Applying the Combined Use Cases of Shocks and Volatility Multipliers:

We have developed the more elaborate credit portfolio outlined below in our earlier credit risk research, which is more similar to what a bank's large-corporate and SME credit portfolio would look like:

Portfolio Size (Bil £)	43
Facility Count	2,018
Regional Composition (limits)	
NORTH AMERICA	54%
UK	46%

Market Segment Composition (limits)	
LC	62%
SME	38%

Facility-type Composition (limits)	
Term	38%
Revolving	38%
Backstop	21%
Contingent	3%

Industry Composition (limits)	
AEROSPACE AND DEFENSE	3%
AGRICULTURE	6%
BANKING	7%
BASIC INDUSTRIES	5%
BUSINESS AND CONSUMER SERVICES	13%
CHEMICALS AND PLASTIC PRODUCTS	2%
CONSTRUCTION	7%
CONSUMER PRODUCTS	3%
FINANCE, INSURANCE AND REAL ESTATE	6%
HOTELS AND LEISURE	5%
MACHINERY AND EQUIPMENT	5%
MEDIA	4%
MEDICAL	5%
METALS	2%
MINING	5%
MOTOR VEHICLES AND PARTS	2%
OIL AND GAS	5%
RETAIL AND WHOLESALE TRADE	5%
TECHNOLOGY	5%
TRANSPORTATION	4%
UTILITIES	3%

TTC Grade/PD Composition (limits)		
AAA	1%	0.01%
AA	1%	0.02%
A+	4%	0.04%
A	6%	0.05%
A-	6%	0.06%
BBB+	8%	0.12%
BBB	8%	0.17%
BBB-	12%	0.27%
BB+	10%	0.51%
BB	10%	0.72%
BB-	9%	1.49%
B+	8%	2.42%
B	7%	4.04%
B-	7%	6.61%
CCC+	3%	11.03%
CCC	1%	22.63%

Authors

Scott D. Aguais, *Managing Director and Founder*, has over 30 years' experience developing and delivering advanced credit analytics solutions for large banking institutions. He led the successful Basel II Waivers at Barclays Capital and RBS, including leading the industry in implementing the first advanced Dual Ratings approach using both Point-in-Time (PIT) and Through-the-Cycle (TTC) risk measures. He then established the Z-Risk Engine ('ZRE') solution which uses the PIT/TTC methodology to support IFRS9/CECL and Stress Testing. A recent Case Study at DBS bank in Singapore outlines their implementation and business benefits of using ZRE. Dr Aguais holds a PhD in Economics.

Lawrence R. Forest Jr., *Global Head of Research*, leads all of ZRE's credit risk analytics research, model development and design. Dr. Forest has over 30 years', experience, designing and developing advanced credit analytics solutions for large banking institutions, including leading the design of the first advanced PIT/TTC Dual Ratings for Barclays Capital, RBS and ZRE. He led the econometric design and development of advanced Basel 2 PD, LGD and EAD credit models and most recently the application of ZRE to assessing climate driven credit risks. Dr Forest holds a PhD in Economics.

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