Integrated Climate Stress Testing Overview: Introducing Firm-Level Climate Risk Sensitivity into Climate Credit Factor Simulations[1]

1. Overview:

Our recent climate stress test research has focused on developing climate 'risky' scenarios that account for the key empirical drivers of observed systematic credit risk by applying detailed multi credit factor models with rising climate related volatility. These papers have highlighted the key role of systematic credit risk shocks historically and have suggested climate change will add to expected future volatility. For climate models developed to-date generally:

- observed past systematic credit risk shocks and volatility have not yet been incorporated in mainstream climate stress test scenarios.
- No direct statistical relationship between climate impacts (rising Global Mean Temperatures (GMT)) and economic risk measures (volatility), have been observed.[2]

Therefore, we have suggested the application of a solid empirical credit factor foundation is a key building block for developing 'risky' climate stress scenarios.

In contrast to dedicated credit factor models, most climate stress test efforts which leverage the well-known NGFS scenarios, have focused on introducing firm-level climate change sensitivity. These company models are usually focused on PD and are based on GHG emissions data related to future carbon transition risk impacts and company location(s) information to assess physical risks. Extensive research by the European Central Bank ('ECB') is a key example of the application of these types of firm-level climate models that apply emissions and geo-location impacts to assess firm-level climate sensitivity.[3]

We see the assessment of firm-level climate sensitivity like the ECB approach driven by NGFS scenarios as a key building block, which has also been supported by suggested high-level BCBS firm-level climate stress scenario requirements.[4] Therefore, a fully integrated climate stress test framework that can support multiple bank regulatory and risk use cases would combine these two building blocks.

This overview outlines an approach for integrating these two scenario building blocks: 'ECB-style', firm-level climate adjusted credit models; and industry and region credit factor models with climate-sensitive volatilities

This note provides a preview of our more detailed, forthcoming Oxford CGFI Working Paper on this topic to be published in October.[5]

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

2 See, Aguais and Forest, (2023 b) for a preliminary assessment of the empirical relationship between rising trends in observed GMT and measures of economic risk.

3 See, Algoskoufis, et. al. (2021) and, ECB (2021).

4 See, BCBS (2022) for a discussion suggested, high-level regulatory requirements for developing climate-adjusted credit models.

5 'CGFI' is the Oxford University UK Centre for Greening Finance and Investment, climate research institute where S. Aguais is an Associate Research Fellow.

info@z-riskengine.com

2. ZRE's Climate Sensitive Models Apply Industry and Region Volatilities:

This note describes a way of introducing firm-level climate-change sensitivity into the determination of credit PD, LGD, EAD, and credit-loss (CL) climate simulations (sims). In doing this, Z-Risk Engine's (ZRE's) climate-sensitive, credit factor models will draw on the PD models assessing individual-company location(s) and emissions data that others including the European Central Bank (ECB) have applied in estimating variations in climate-change risk.[6]

Up to now, the ZRE climate change stress credit models have:

- started with an overall average upward trend in credit-factor vols based on an assumed relationship to the rising global mean temperatures (GMTs) in NGFS climate scenarios,[7]
- distributed this overall average, vol trend to industry and region groupings based on industry and region 'carbon intensity betas,' and,
- assigned each firm in each industry-region segment the same industry-region vol trend as other firms in that segment.

Under a climate-change scenario, the rising vols lead to a wider range of 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. In this case, the losses in high-percentile stress simulations are greater than in the absence of climate change. Further, one can assess the impacts of climate change by running climate credit simulations with and without the volatility multipliers and carbon intensity betas.

This ZRE factor approach has not yet included the possibility of differences arising from climate-adjusted PD models that assess varying locations and GHG emissions of firms within each segment. This motivates a more integrated approach.

In a combined model approach, we would incorporate firm-level climate sensitivities by:

- starting again with a global average upward trend in credit-factor vols based on an assumed relationship to the rising GMTs in a climate scenario, and,
- distributing the global average vol trend directly to individual firms based on 'ECB-style' climate-adjusted PD models each of which implies a particular exposure to physical risk (location), and their GHG emissions, which translate into transition risk.

Under this approach, we apply firm-level beta coefficients derived from ECB-style models to average global sensitivities or as well, to differential industry/region volatilities. The firm's specific climate betas will have an average value of one. Firms with greater (lesser) than average exposures to climate-change risks will have betas above (below) one. The firm-level beta applied to the global average volatility multiplier will yield a firm volatility multiplier. Under this combined approach, the firm's industry and region may also have roles in determining the firm beta, but locations and emissions modelled in NGFS-driven PD model scenarios will play the key role.

6 The firm-level climate-adjusted credit models that are part of this integrated approach could be sourced from internal bank development of 'ECB-style' credit models or from those provided by climate risk vendors or consultants so the approach is quite flexible.

7 We are continuing our research to develop a more empirically based calibration for this illustrative climate volatility relationship.

3. Flexible Integration Will Combine Firm-Level Climate Models With ZRE:

The proposed climate model architecture would combine climate-adjusted PD credit models developed by banks internally, or by vendors or consultants directly with the ZRE detailed industry/region credit factor climate simulations. Ultimately, an integrated model calibration would need to be developed across the combined climate related credit factor sensitivities and the firm-level climate-adjusted PDs.

For the global average volatility calibration, we plan initially to continue using the same illustrative formula found in our existing models until we develop a broader volatility calibration. To assess firm-level climate sensitivity (betas), we plan to set them based on relative DD ($=-\Phi^{-1}$(PD)) where 'DD' is default distance changes estimated by an existing climate-sensitive, cost-based ECB-style PD model. Therefore, we plan to replace the illustrative sector carbon intensity betas developed in our climate research notes with specific firm-level climate sensitivity betas.

To develop firm-level betas, suppose that, in a climate scenario, a cost-based PD model projects a fall in DD in 2050 from its current value of 15 percent for company A, 7.5 percent for company B, and 10 percent 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 0.75. If in the year 2035 in that scenario, the fall in DD was 11 percent for company A and 7 percent for the global average company. In this case, company A's beta for 2035 in that scenario would be 1.57. Green technology improvements could also drive systematic reductions in costs and therefore reduce firm PDs over time.

4. Implementing ECB-Style Firm Climate Models as 'TTC Drift' in Climate Stress Scenarios:

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 CO2 and other GHGs. Some climate-scenario approaches 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.[8] For such companies, incomplete cost passthrough causes profitability to trend down, book leverage to increase, and defaults and credit losses to drift up. We explain below how we can incorporate this into our climate-scenario models.

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 the exposures in the representative, credit portfolio drift up. *We call this 'TTC Drift.'*

We refer to these climate-driven, systematic firm-level PD changes as 'TTC Drift' because generally observed, long-run TTC PDs for given credit grades (internal or Agencies) or for EDF-derived industries/region credit factors do not normally reflect rising or falling

8 The latest ECB climate stress methodology (2023) has suggested changes in cost-passthrough assumptions for non-energy and energy related costs relative to the 2021 methodology paper. Based on our initial review, instead of assumed cost increases as partially passed through in general, the latest ECB approach seems to suggest non-energy costs are fully passed through and energy-related costs are not passed through and are therefore borne directly by producers. In ours and other's opinions these assumptions remain inconsistent with published historical cost-passthrough studies.

info@z-riskengine.com

systematic trends. Therefore, systematic climate impacts on individual firms can be described as ‘TTC Drift’ relative to historically observed TTC PD behavior.

In our recent Climate Risk Stress Test Research Note Three (2023, c) we previewed our approach for integrating ‘TTC Drift’ at the firm-level by implementing ‘TTC Drift’ (**Figure 1**) using aggregate PD shifts. For this we allow the weights on the different credit grades to shift slowly over time, diminishing in the lower risk grades (e.g., A and BBB) and increasing in some of the higher risk ones (B and CCC). In this example, the weight shift produces a change over 2020-2050 in the overall, TTC PD about the same as that projected by the ECB model in the most severe, NGFS Hot House scenario.

2050 TTC parameters without drift

Inputs							
Weight	Entity Grade	Facility Type	Limit in $s mm	EU	PD$_{TTC}$	LGD$_{TTC}$	CCF$_{TTC}$
10.0%	A	RCF	300	10%	0.01%	35%	75%
		TL	300	100%		35%	100%
25.0%	BBB	RCF	300	20%	0.03%	30%	45%
		TL	300	100%		30%	100%
45.0%	BB	RCF	300	30%	0.14%	30%	45%
		TL	300	100%		30%	100%
15.0%	B	RCF	300	30%	0.97%	25%	45%
		TL	300	100%		25%	100%
5.0%	CCC	RCF	300	50%	6.84%	20%	45%
		TL	300	100%		20%	100%
100.0%	All	All	600	63%	0.56%	23%	73%

2050 TTC parameters with drift: hot house scenario

Inputs							
Weight	Entity Grade	Facility Type	Limit in $s mm	EU	PD$_{TTC}$	LGD$_{TTC}$	CCF$_{TTC}$
9.5%	A	RCF	300	10%	0.01%	35%	75%
		TL	300	100%		35%	100%
24.5%	BBB	RCF	300	20%	0.03%	30%	45%
		TL	300	100%		30%	100%
45.2%	BB	RCF	300	30%	0.14%	30%	45%
		TL	300	100%		30%	100%
15.5%	B	RCF	300	30%	0.97%	25%	45%
		TL	300	100%		25%	100%
5.3%	CCC	RCF	300	50%	6.84%	20%	45%
		TL	300	100%		20%	100%
100.0%	All	All	600	64%	0.58%	23%	73%

Figure 1: 2050 Weights on Different Risk Grades With and Without TTC Drift
Source: See, Aguais and Forest (2023, c)

In a climate-adjusted PD model that draws on firm-level data on emissions and location and on estimated drifts in TTC PDs, we would implement ‘TTC Drift’ at the level of the representative firm rather than rating grade.

One should note that an upward drift in the TTC PDs of the representative portfolio contradicts the usual fixed-risk-appetite assumption intrinsic to most short-run traditional stress test credit scenarios.

If one continues to apply this assumption, the upward drift in TTC PDs would for the most part be reduced. This implies that businesses in their financing decisions and banks in their portfolio structuring would act to reduce leverage by enough to offset rising vols. Therefore, the industry needs to better understand the complexities of how developing long-run climate ‘risky’ scenarios with firm-level PD adjustments through ‘TTC Drift’ will be integrated with broader risk appetite assumptions and the application of dynamic net-zero business strategies.[9]

9 Our forthcoming Oxford CGFI paper will discuss these complexities in detail.

5. Summary:

We see two key, integrated building blocks for developing climate scenarios subject to future physical and transition risks. The first building block has been suggested by regulators (ECB) and the BCBS, that have proposed adjustments to firm-level PD credit models based on firm's GHG emissions and the geo-location of key physical assets and operations. Detailed NGFS scenarios and related SSP pathways play a key role in driving these proposed model climate adjustments. To-date however, the suggested impacts of climate risk in these models have usually suggested limited impacts.

In our climate research papers we have proposed a second key climate risk scenario building block that adds potential climate related systematic volatility through a dedicated credit factor approach developed from market based EDF measures of credit risk. Therefore, a fully integrated climate model architecture for developing short and long-run climate scenarios would combine these two climate scenario building blocks in a single model architecture. Our forthcoming Oxford CGFI paper will explain this integrated approach in detail, review various scenario model methodologies, and present integrated climate scenarios applied to a UK/European credit portfolio.

info@z-riskengine.com

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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 and is an Associate Research Fellow at the University of Oxford CGFI climate institute, collaborating on further climate risk research.

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.

Developed by Aguais And Associates Ltd, Z-Risk Engine® (ZRE) provides a highly accurate, centralised, and integrated solution supporting global bank's compliance for IFRS9, CECL and Stress Testing regulations. ZRE is also being adapted to support Climate Stress Testing.

ZRE is a proven and efficient route to regulatory compliance for CROs and CFOs that also delivers up to a 30% reduction in IFRS9 modelling operational costs. As an advanced suite of Python or SAS® based software that works with a bank's own IRB wholesale internal credit models, ZRE unlocks complex industry and regional credit cycles to accurately convert TTC PD, LGD and EAD models into PIT measures. Whilst lowering implementation risk, the solution is also highly configurable and customisable to support large bank's detailed portfolio mix of commercial, corporate and bank clients.

info@z-riskengine.com

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