

# Developing Climate Scenario Impacts on Credit Models – Applying the ECB Climate Stress Test Approach Through ‘TTC PD Drift’<sup>1,2</sup>

## 1. Overview:

In our recent climate change Frontiers paper (2023, a) and climate risk research notes (2023 b, c) we developed two separate *use cases* for deriving long-run climate stress test (‘CST’) scenarios based on a multi credit-factor framework. The industry and region, credit factors and correlations in this approach derive from 32 years of market based EDFs.<sup>3</sup> We also demonstrated in our ‘Hockey Stick’ note that there’s not as yet, a statistically significant relationship observed between climate change, as measured by rising global mean temperatures (‘GMT’), and financial risks, as gauged either by market- or credit-factor volatilities. Therefore, in the first two *use cases*, rather than applying an observed empirical association, we *assumed* that a relationship between GMT and credit risk would arise in the future. On this basis, we developed climate-change, credit scenarios by either:

- specifying a hypothetical, functional relationship in which credit-factor volatilities rise in proportion to GMT expressed relative to the 1990-2022, average GMT value, or
- assuming that, at selected, future dates, climate related, credit shocks could occur with magnitudes similar to past moderately large, non-climate credit risk shocks.

In this Climate Research Note we develop a third CST *use case*. This involves the application of smooth declines in company creditworthiness foreseen by the recent ECB (2021) CST model. According to this model, physical damage and transition events associated with climate change cause business costs to rise, profitability to fall, leverage to increase, and defaults and credit losses to drift upwards. Similar to the changes portrayed in the NGFS scenarios, these effects occur gradually and not, as in most credit models and the first two, *use cases*, as sudden unexpected shocks. For another example, outlining application of the general ECB CST approach, see Elste et. al., (2022).

Here, we mimic the ECB approach by having the through-the-cycle (TTC) PDs of companies in a credit portfolio rise on balance at the rates foreseen by the ECB model in specific NGFS scenarios.<sup>4</sup> We refer to these gradual increases in TTC PDs as ‘TTC Drift.’ We set the drift overall for the representative, example C&I portfolio to rates that replicate the ECB model’s estimates for a median company. While the simplified results presented here don’t include this, our model, allows us to apply the carbon-intensity betas introduced in our earlier research note (2023 c) in distributing the drift differentially to

- 
- 1 ‘TTC Drift’ refers to through-the-cycle PDs which ‘drift’ upward over time based upon climate impacts.
  - 2 The ZRE research presented in this Climate Research Note is preliminary, all feedback and comments welcome, any errors or omissions remain the responsibility of the authors.
  - 3 We use Moody’s CreditEdge as the source of the EDFs, see, Moody’s, (2016).
  - 4 In applying the TTC Drift use case below we use the stylized credit portfolio we developed in the Credit Risk Triptych and Frontiers papers, which is summarized in **Appendix I**.

industry sectors.<sup>5</sup> Here, for simplification purposes, to illustrate application of the ECB approach in the Z-Risk Engine scenario capability we apply the same rates of drift for each industry. We then identify the climate related TTC-drift impacts for relevant NGFS ECB-model scenarios as the difference between the portfolio losses in a ‘No Climate Effects’ scenario with and without TTC drift.

The impacts are small, and close to negligible. This mirrors the ECB model’s estimates that show, even in the most severe NGFS, “Hot House” scenario, that the overall median PD of companies in 2050 exceeds the baseline, Orderly Transition value by only about 5.5%.<sup>6</sup> In our scenarios, we assume that the PD estimated for 2020 from the US Bank C&I loss data corresponds to that baseline PD.

We now review some broad issues concerning climate scenarios.<sup>7</sup>

### **Fixed Portfolio Approach Seems to Rule Out Climate-Change Impacts**

As a tractable way of anticipating future dynamic portfolios, regulators generally instruct banks to assume a ‘fixed portfolio’ in running short-run baseline and stress scenarios, see EBA (2022).<sup>8</sup> We interpret this as a requirement that the credit portfolio applied during scenarios will have fixed, TTC attributes, meaning that the maturities, industry and region associations, and TTC PDs, LGDs, and EADs of each exposure in the portfolio remains constant at the values observed at the last date prior to the start of the scenario. This, however, would seem to rule out climate change having any effect on a portfolio’s TTC risk over time.

### **Static Technology Assumptions Exclude a Central Feature of Climate-Change Economics**

Climate change has been and will continue to be addressed through invention and implementation of new, carbon-lite technologies. But economics has been unable to foresee anything specific about technological change. Instead, technological advance appears as a statistical residual in economic growth accounting. As a result, predictions of the structural and economic effects of climate change remain murky. However, in an effort to get detailed forecasts, many models assume close to static technology and in some, most extreme cases, fixed input-output coefficients.

---

5 The ECB approach in general is applied to individual company financials and then aggregated to industries and the aggregate PD increase to 2050. While our illustration of the TTC Drift use case presented here is applied on a top-down basis for illustration purposes, our approach is general and could therefore, also be applied on a bottom-up or industry basis derived from the company climate adjusted financial models’ banks and the industry are currently working on.

6 See ECB, Algoskoufis (2021) page 44 for a discussion of the median PD impact for the NGFS Hot House scenario. In our application of the TTC Drift use case below, we use the FRB C&I loss index as a benchmark, so for consistency we scale up the PD we apply to 2050 to 9-10 bps as compared to the ECB 5.5%.

7 These broad issues are general to CST approaches and while only highlighted here, we will discuss them in more detail in a forthcoming climate change working paper.

8 See, EBA (2022) section 1.3.8, for a discussion of applying a static balance sheet assumption in short-run stress tests.

## **Some Models Rely on Unconventional Assumptions of Less-than-Full Cost Passthrough**

Some CST models view climate change as eroding the creditworthiness of businesses through incomplete passthrough of rising costs, particularly carbon costs. This is the case in several approaches, including the ECB one that motivates our TTC-drift estimates.

In these models, partial cost passthrough implies shrinking profit margins and hence rising probabilities of default (PDs). However, under the standard assumption that broad-based cost increases get passed through in higher prices, both profit margins and PDs would remain unchanged. Past experience, see de Bruyn (2015), supports this standard assumption of full or nearly full cost pass-through, since otherwise one would have observed divergence in PD trends, rising in sectors with increasing relative costs including oil and gas and decreasing in sectors with decreasing relative costs. Instead, in all sectors, we observe basically trendless PDs, consistent with full, cost passthrough.

## **Contrary to Empirical Evidence, Models Assume that Credit Losses Occur Without Shocks**

Consistent with past observation, the standard Merton default model traces defaults and credit losses to unexpected shocks. The shocks may be idiosyncratic, specific to a firm, or systematic, shared by many firms.

In such models, expected trends in cash flows and asset values give rise to the same trends in indebtedness, implying little or no change in PDs. However, if cash flows and asset values unexpectedly plunge below trend, providing insufficient time for businesses to adjust, profits get squeezed, leverage spikes, and defaults become more likely. Surprisingly, many climate-change credit models have made simplifying assumptions that mostly exclude these features of the standard, credit models informed by historical experience. Instead, many climate models attempt to trace credit impacts on businesses to gradual, predictable declines in trend growth (see NGFS) or rises in input costs. In the Merton model, such changes lead to compensating adjustments in indebtedness, with limited if any effect on defaults and credit losses.

## **Some Climate Models Apply Close-to-TTC PD Formulas**

Under the Merton model, PDs of businesses are functions of mark-to-market (MtM) leverage and leverage volatility. As in the Moody's CreditEdge EDF model (2016) and in several other, similar, public-firm PD models, one applies the Merton approach to listed companies by drawing on Black-Scholes-derived measures of MtM asset values and asset volatilities and book-value measures of debt.

In extending this approach to unlisted companies, one may include as PD-model inputs both company accounting measures of leverage and volatility and industry and region, summary measures (Z factors) of listed-companies, using MtM, default-distance (DD = leverage/volatility). This is the 'Z' approach we have taken in our long-time work developing PIT credit models at the banks where we have worked, and which is implemented in the Z-Risk Engine solution.<sup>9</sup>

---

<sup>9</sup> Our roughly 15 research papers on this approach can be found on [www.z-riskengine.com](http://www.z-riskengine.com).

By improving the fit to cyclical fluctuations, such DD indexes (‘Zs’) increase the explanatory power of the PD models substantially. One finds this Z index-based approach applied in both the Z-Risk Engine models and in Moody’s, Credit-Cycle-Adjusted, private-firm model.<sup>10</sup> Despite well-informed, credit analysts being familiar with these results, many climate-change, credit models involve PD functions without the Merton model’s usual logical foundation or market-value-related inputs.

### ECB Model Has Offsetting Weaknesses

In summary, we have general concerns that the ECB approach that assumes that slowly upward trending costs would be only partially passed through into prices, is less than realistic. Instead, since the climate scenarios involve increases in cost trends, but not in the magnitudes or frequencies of systematic shocks, we’d expect businesses to adapt to those cost changes, fully passing them through, and achieving broadly unchanging profitability, specifically the profitability required as compensation for the unchanging, systematic volatility generally observed.

In addition, on the issue of PIT vs TTC PD credit models, the PDs arising from the formula in the ECB model (mostly TTC) would surely be more insensitive to systematic changes in economic conditions. Although fit to CreditEdge EDFs, which are highly sensitive PDs, the formula itself excludes from its explanatory variables the critical, CreditEdge inputs of market leverage and volatility.<sup>11</sup> Instead, with only book-value-financial and national-account variables as inputs, the PD function would, as in the case of the Moody’s, Financial-Statement-Only, RiskCalc model, produce PDs that substantially understate broad-based variations including any attributable to future climate change.

Ironically, the two shortcomings above tend to be somewhat offsetting and so it may be the case that the ECB model produces reasonably plausible estimates of climate-change’s effects on corporate defaults – *excluding the impacts of volatility and unexpected shocks*. In any case, the estimates indicate very small impacts. In the most extreme, NGFS Hot House scenario, the ECB model shows the median-firm’s PD in 2050 exceeding the baseline Orderly Transition Scenario by about 5.5%.<sup>12</sup> For the US bank, C&I portfolio, we estimate a 2020 PD of about 1.73%.<sup>13</sup> We derive this estimate by dividing the reported, 2020, C&I charge-off rate of 0.52% by an approximate LGD of 30%. Thus, for this portfolio, the ECB model projects a 2020-2050 increase in PD in the NGFS Hot House scenario of about 9.7 bps (= 5.5% x 1.73%).

---

10 See Dwyer et. al. (2009).

11 See ECB (2021) Appendix B, page 80.

12 See ECB (2021), page 44.

13 See Board of Governors of the Federal Reserve System, (2022).

## 2. Overview: Implementing a ‘TTC Drift’ Climate Stress Test Use Case:

Here we develop examples of the TTC Drift climate scenario *use case* that includes:

- Running Z sims with volatilities held fixed at values estimated historically to derive the ‘No Climate’ Scenario, and
- Having the TTC PDs of the C&I portfolio increase to 2050 relative to 2020 by about 9.7 bps in the NGFS Hot House Scenario and by about 4 bps in the Disorderly Transition Scenario.

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 greenhouse gases (GHGs). Some climate-stress models including the one developed by the ECB (2021) assume that businesses only partly pass through these gradually rising costs. This causes profitability to trend down, book leverage to increase, and defaults and credit losses to drift up.

### A. Introducing TTC Drift into Climate Scenarios:

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 illustrative credit portfolio we applied in the Triptych and Frontiers papers drift upward. We call this ‘TTC drift.’ See below one way of implementing TTC drift (**Figure 1**). Here 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 horizon in the overall, TTC PD about the same as that projected by the ECB model in the most severe, NGFS Hot House scenario, after scaling to be consistent with the FRB C&I benchmark portfolio of about 9–10 bps.

2050 TTC parameters without drift								2050 TTC parameters with drift: hot house scenario							
Inputs								Inputs							
Weight	Entity Grade	Facility Type	Limit in \$ mm	EU	PD <sub>TTC</sub>	LGD <sub>TTC</sub>	CCF <sub>TTC</sub>	Weight	Entity Grade	Facility Type	Limit in \$ mm	EU	PD <sub>TTC</sub>	LGD <sub>TTC</sub>	CCF <sub>TTC</sub>
10.0%	A	RCF	300	10%	0.01%	35%	75%	9.5%	A	RCF	300	10%	0.01%	35%	75%
		TL	300	100%		35%	100%			TL	300	100%		35%	100%
25.0%	BBB	RCF	300	20%	0.03%	30%	45%	24.5%	BBB	RCF	300	20%	0.03%	30%	45%
		TL	300	100%		30%	100%			TL	300	100%		30%	100%
45.0%	BB	RCF	300	30%	0.14%	30%	45%	45.2%	BB	RCF	300	30%	0.14%	30%	45%
		TL	300	100%		30%	100%			TL	300	100%		30%	100%
15.0%	B	RCF	300	30%	0.97%	25%	45%	15.5%	B	RCF	300	30%	0.97%	25%	45%
		TL	300	100%		25%	100%			TL	300	100%		25%	100%
5.0%	CCC	RCF	300	50%	6.84%	20%	45%	5.3%	CCC	RCF	300	50%	6.84%	20%	45%
		TL	300	100%		20%	100%			TL	300	100%		20%	100%
100.0%	All	All	600	63%	0.56%	23%	73%	100.0%	All	All	600	64%	0.58%	23%	73%

**Figure 1: 2050 Weights on Different Risk Grades with and without TTC Drift**

Sources: ECB and Z-Risk Engine assumptions motivated by Long Run Average PDs and US Bank C&I Loss Rates

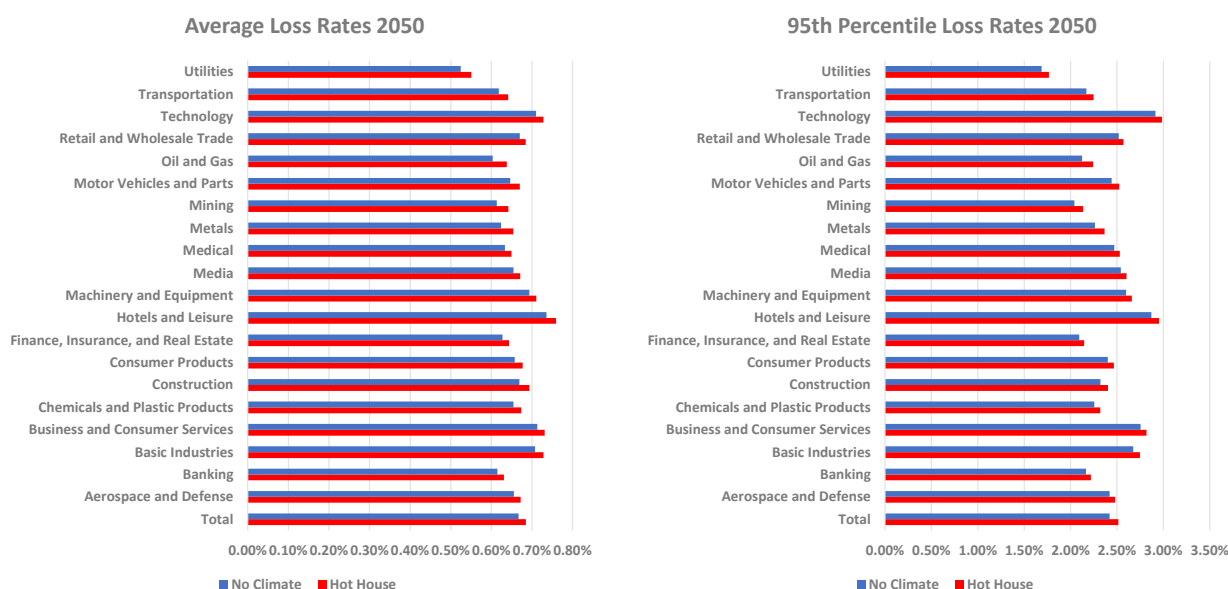
### B. Loss Results in Selected, TTC Drift Scenarios:

Introducing TTC drift this way and calibrating it to replicate the ECB model’s estimates of median PD increases in various scenarios, we obtain credit losses only modestly higher than those in the no-TTC-drift case (**Table 1**). These climate scenarios assess deterministic, TTC drift effects as compared with the random, credit-cycle variations implied by the no-climate-effects, credit-risk-factor simulations.

PORTFOLIO	LOSS RATE STATISTIC	TTC DRIFT SCENARIO		
		No Drift	ECB Disorderly Transition	ECB Hot House
US Bank Commercial and Industrial Loans	Mean	0.67%	0.68%	0.70%
	95th Percentile	2.31%	2.34%	2.39%

**Table 1: Comparison of Loss Rates for 2050 in Different TTC-Drift Scenarios**  
Sources: Z-Risk Engine analysis and ECB (2021)

The loss estimates involve varying effects by industry. These varying industry effects derive from the differences in observed industry sector factor volatilities but not from additional impacts of applying carbon sensitivities, which we will add in further climate research. In any case, due to the small size of the average drift, we obtain only small variations across the various industry sectors.



**Figure 2: Industry Loss Rates in ECB Hot House Scenario**  
Sources: NGFS, ECB and Z-Risk Engine analysis.

To develop a third CST use case within our climate stress test solution, we have outlined above an approach for applying aggregate PDs derived from current climate models such as the ECB approach. The channels in these models through which climate impacts are felt are primarily through changes to borrower creditworthiness, most directly applied to company PDs. These models have been applied to individual companies through changes in related climate costs from physical risk impacts and future carbon mitigation policies.

As the BCBS ‘Frequently Asked Climate Questions’ (2022) outlines, regulators are moving in the direction of requiring banks to assess and apply potential climate impacts initially through climate effects that are integrated with credit models directly. The ECB CST research provides an example of this type of approach and banks, and the industry are developing initial borrower-level climate models along these lines.

Our illustration of the TTC Drift CST *use case* suggests a way to apply and integrate these borrower-level climate risk adjustments within a broader credit-factor model. In our CST framework, we apply multiple *use cases* for assessing a range of future climate stress scenarios.

The overall CST approach we have developed, especially for deriving long-run climate scenarios, is focused on the detailed industry and region credit factors that drive systematic risk in general. *We suggest that simulating the credit factors over long, time horizons, is substantially better than trying to project individual company climate-adjusted financials over long time horizons to 2050.*

For assessing short-run (1-5 years) climate change impacts, the primary regulatory approach, see ECB (2021) and the BCBS (2022), is focused on adjusting bank credit models for physical risk and the impact of carbon mitigation climate policies. However, short run scenarios of 1-5 years may reflect economic influence more so than climate impacts as climate is more of a longer run phenomenon. To assess short and long-run climate risk impacts, banks most likely will need an integrated framework applying both short run models like those assessing company creditworthiness as well as longer-run credit factor scenario models. Therefore, this third *use case* demonstrates a way to integrate PD impacts derived in the ECB approach with long run scenarios that also could incorporate future volatility and climate related shocks.

## Summary:

This Climate Research Note describes an additional climate stress test *use case* we are adding to our climate risk solution that is modelled on company-level climate impacts consistent with the research underway, for example at the ECB. We apply the impacts of climate risk on company creditworthiness (PDs) through the concept of TTC Drift that is integrated into climate scenarios based upon adjustments to credit models. TTC Drift refers to the upward (deterministic) shift over time in non-cyclical wholesale borrower PDs. To calibrate the effect of TTC Drift we have illustrated this *use case* with future climate related PD increases as suggested by the ECB climate research. In principle, the TTC Drift *use case* could be calibrated to any climate-adjusted credit models developed by regulators, vendors or by individual banks.

TTC Drift impacts derived from company-level credit model adjustments could also be applied in our CST approach through adjustments to industry sector PDs using our sector credit factors. For illustration purposes we have applied the TTC Drift example on a top-down basis.

As suggested above, we believe however, that projecting climate risk impacts on individual company financial data over 25-year time horizons is not the best approach for developing long-run climate risk scenarios. Therefore, a fully integrated CST framework could incorporate company-level climate models through the TTC Drift *use case* with longer-run credit-factor based scenarios that fully reflect future uncertainty.

## Bibliography:

Alogoskoufis, S., et. al., (2021), ‘ECB economy-wide climate stress test Methodology and results’, European Central Bank, Occasional Paper Series, No 281, September.

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](http://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](http://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](http://www.z-riskengine.com), November.

Aguais S. and L. Forest, (2023, a), ‘Climate-Change Scenarios Require Volatility Effects to Imply Substantial Credit Losses–Shocks Drive Credit Risk Not Changes in Economic Trends’, Decision Making for the Net Zero Transformation: A Compendium of Best Practice, [www.frontiersin.org](http://www.frontiersin.org).

Aguais, S. and Forest, L. (2023 b), ‘The Climate Change ‘Hockey Stick’ is Observable–But Climate Change Impacts on Economic Risks are Not Yet Observable’, Z-Risk Engine, Climate Stress Testing Research Note NUM One, March.

Aguais, S. and Forest, L. (2023 c), ‘Assessing Climate Related ‘Socio-Economic Tipping Point’ Risk Impacts by Applying Credit-Factor Shocks, Z-Risk Engine, Climate Stress Testing Research Note Num One, April.

Baer, M., et al., (2023), ‘TOWARD A FRAMEWORK FOR ASSESSING AND USING CURRENT CLIMATE RISK SCENARIOS WITHIN FINANCIAL DECISIONS’, UK Centre for Greening Finance and Investment, Discussion Paper, March.

Basel Committee on Banking Supervision (2022), ‘Frequently asked questions on climate related financial risks’, BIS, December.

Board of Governors of the Federal Reserve System (2022), ‘Charge-off and delinquency rates on loans and leases at commercial banks’, <https://www.federalreserve.gov/releases/chargeoff/chgallsa.htm>.

de Bruyn, S. M., et al., (2015), ‘Ex-post investigation of cost pass-through in the EU ETS: An analysis for six sectors’, European Commission, Directorate-General for Climate Action, November.

Dwyer, D. and D. Eggleton, (2009), ‘LEVEL AND RANK ORDER VALIDATION OF RISKCALC V3.1 UNITED STATES’, Moody’s Analytics White Paper, September.

EBA, European Banking Association (2022), ‘2023 EU-Wide Stress Test - Methodological Note’, November.

ECB economy-wide climate stress test, Methodology, and results, (2021), European Central Bank, Occasional Paper Series number 281. ECB September.



Elste, F., M. Kalkbrenner and L. Popkin, (2022), ‘Climate Stress Testing – Introduction and recent experiences’, Deutsche Bank Chief Risk Office, presentation to RiskMinds International, Barcelona, November.

Moody’s Analytics (2016), ‘CreditEdge: A Powerful Approach to Measuring Credit Risk, Brochure’. <https://www.moodyanalytics.com/-/media/products/CreditEdge-Brochure.pdf>.

## Appendix I: Illustrative Credit Portfolio Used in Applying ‘TTC Drift’:

Here we summarise the credit portfolio data used in applying TTC Drift:

**Table 1: Industry Composition of the Representative C&I Portfolio**

Weight	C&I Industry	Associated Region Grouping
1%	Aerospace and Defense	North America Corps
5%	Banking	North America Fls
5%	Basic Industries	North America Corps
20%	Business and Consumer Services	North America Corps
2%	Chemicals and Plastic Products	North America Corps
10%	Construction	North America Corps
2%	Consumer Products	North America Corps
10%	Finance, Insurance, and Real Estate	North America Fls
5%	Hotels and Leisure	North America Corps
3%	Machinery and Equipment	North America Corps
5%	Media	North America Corps
5%	Medical	North America Corps
1%	Mining	North America Corps
5%	Motor Vehicles and Parts	North America Corps
3%	Oil and Gas	North America Corps
6%	Retail and Wholesale Trade	North America Corps
4%	Metals	North America Corps
4%	Technology	North America Corps
3%	Transportation	North America Corps
1%	Utilities	North America Corps
100%	All	All

The representative credit portfolio in the scenarios is designed for illustration purposes and includes a mixture of revolving (RCF) and term loan (TL) facilities. The total limits for the portfolio in RCFs and TLs are \$300 million each for a portfolio of \$600 million in total. The size of the portfolio is mostly irrelevant as the focus in these empirical assessments is on changes in expected credit loss rates. Table 2 below shows, the 5 broad risk grades utilized and the related PDs, LGDs and EADs which are further described below. As the benchmark index used to assess various potential credit losses is derived from the Federal Reserve Board’s published US C&I loss index, we apply only one region Z, for NA.

The \$600 million portfolio is then distributed to the 5 entity risk grades using the weights shown in Table 2 and to the 20 industry sectors using the weights shown in Table 1. To simplify the model, we assume that the TTC attributes are fixed over time and are the same for every industry-region segment.

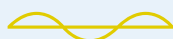
**Table 2: TTC Risk Attributes of Facilities Within Each Industry-Region Grouping**

Weight	Entity Grade	Facility Type	Primary Region	Primary Industries	Expected Utilization	1-Qtr PDDTTC	LGD TTC	CCFTTC	FCF								
10%	A	RCF	North America	All Industries	10%	0.01%	35%	75%	1.00								
		TL			100%		35%	100%									
25%	BBB	RCF			North America	All Industries	20%	0.03%	30%	45%	1.00						
		TL					100%		30%	100%							
45%	BB	RCF					North America	All Industries	30%	0.14%	30%	45%	1.00				
		TL							100%		30%	100%					
15%	B	RCF							North America	All Industries	30%	0.97%	25%	45%	1.00		
		TL									100%		25%	100%			
5%	CCC	RCF									North America	All Industries	50%	6.84%	20%	45%	1.00
		TL											100%		20%	100%	
100%	All	All		All									63%	0.56%	23%	73%	1.00

## 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.



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](mailto:info@z-riskengine.com)**

**[www.z-riskengine.com](http://www.z-riskengine.com)**