CLIMATE CHANGE CREDIT RISK TRIPTYCH[1]

Paper Two: Climate Change Volatility Effects Imply Higher Credit Losses

In this second climate triptych paper we assess climate change impacts on wholesale credit losses to 2050 using the Z-Risk Engine industry and region credit factor Monte Carlo simulation module. To accomplish this, we:

- Select various NGFS global-mean-temperature (GMT) scenarios
- Calculate, for each GMT scenario, climate volatility multipliers using an illustrative GMT-to-Volatility assumption
- Derive, through Monte Carlo simulations for each GMT scenario, estimates of expected, 95%, and 99% 'tail' climate change credit losses for a benchmark USA, C&I credit portfolio
- Find that climate-driven volatility increases lead to larger credit losses especially in severe recession scenarios

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.

1 A triptych is a form of art, made up of three individual panels that form one single painting. Therefore, the idea of a triptych works well to describe these three separate but integrated CST research papers.

* These Draft Working Papers present preliminary research and results - feedback welcome - any errors or omissions remain the responsibility of the authors

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Overview – Triptych Paper Two:

In triptych paper one we provided a review of key industry discussion points for current efforts by financial regulators and the global NGFS consortium to develop Credit Stress Test ('CST') approaches to assess future credit risk Impacts of climate change. CST approaches are generally driven top-down to broadly assess the future welfare cost impacts of volatile climate behaviour. However, smooth, 'stylized' NGFS scenarios are not designed to assess observed systematic unexpected 'economic shocks' which have driven the last three recessions.

In this second triptych paper we apply the ZRE *Industry Region Monte Carlo* ('IRMC') capability to assess the potential impact of increased climate volatility on future credit losses. The ZRE IRMC approach is a well-developed approach for assessing credit losses having been implemented in multiple large banks over the last 15 years. We also pointed out that recent research by Garnier et al, (2022) utilizes a broadly similar approach to the one outlined in detail in our extensive publications since 2005.

The application of ZRE in these climate volatility driven assessments provides an approach that provides better understanding of key CST industry discussion points, including: (1) use of an empirically founded climate credit risk approach, (3) assessment of extreme climate scenarios including empirical assessment of 95% and 99% statistical 'tail' confidence interval credit losses, and (4) application of a detailed, dedicated industry and region sector model.

Assessing Climate Change Volatility Impacts on Wholesale Credit Losses:

A. Introduction:

In most climate scenarios today, climate change slows economic growth, but has little effect on the volatility of the factors influencing credit risk. As a result, climate change in these scenarios has limited impact on credit losses. Here, we assume, contrary to the familiar scenarios, that climate change increases the cyclical volatilities of credit-risk factors. Consequently, in more severe climate scenarios, the economy endures higher credit losses. This unsurprising result resembles the finding that, if climate change produces more extreme, weather events and, as well, more volatile overall economic shocks, then, in more severe climate scenarios, general climate costs will be higher on a global basis.

The credit-loss estimates in this second paper come from Z-Risk Engine's (ZRE's), IRMC module. Following the longstanding, portfolio-credit-risk, modelling approach, the IRMC runs credit-factor ('Z') simulations (sims) that, entered into PD, LGD, and EAD models for each of the facilities in a portfolio, produce portfolio-credit-loss sims. We've modified this model by introducing climate-sensitive multipliers applied to the volatilities of the random shocks that drive the evolution of the Z factors.[2]

2 For clarity we refer in these papers to two kinds of 'shocks' more broadly economic shocks occur in the aggregate for example precipitating the last three observed recessions. More narrowly, we refer to 'statistical shocks' applied in the IRMC that are random and which drive the statistical simulation results.

As the climate warms, those multipliers grow increasingly above one, causing the credit-factor volatilities to rise above historical norms. Applying this climate-sensitive, IRMC model in simulating the credit losses of a representative, US commercial-and-industrial (C&I), loan portfolio, we find that more severe, climate scenarios imply higher credit losses especially in downturns.

The quantitative results in this paper involve an assumed relationship between global mean temperatures (GMTs) and credit-factor volatilities. *Thus far, we have no empirical results to substantiate this or any other relationship between a climate metric and credit-factor volatilities.*[3] *In preliminary research, we have compared the CCAR scenarios on market volatilities with GMTs and have found an insignificant (but positive) correlation*. Thus, the quantitative results presented here remain hypothetical for the GMT driver but robustly statistical in using a fully calibrated credit factor model from Credit Edge EDF history. In future research, we will explore calibrating the climate/credit volatility relationship.

B. Substantial Share of Credit Losses Occur in Crises Missing from Climate Scenarios:

Much of past, credit losses have occurred about once a decade as major spikes caused by sharp, cyclical drops in creditworthiness (**Figure 1**). But the familiar, NGFS, climate scenarios differ only in growth trends, without the kinds of abrupt downturns that account for much of historical, credit losses. Further, the trend differences in the various scenarios are so small as to be nearly invisible in graphical comparisons (**Figure 2**). Thus, these NGFS scenarios suggest that climate change has limited effect on credit losses.

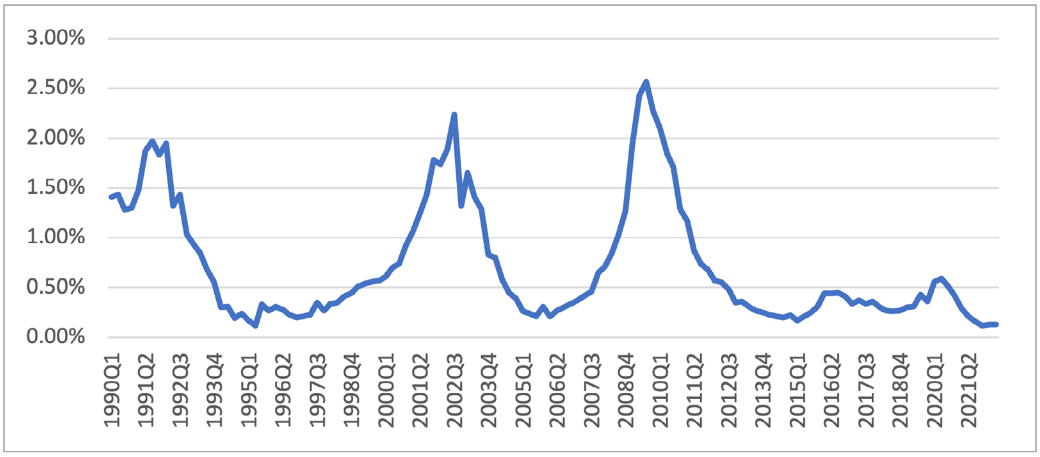

Figure 1: Annualized Charge-Off Rates, US C&I Loans, Quarterly, Seasonally Adjusted

Source: Board of Governors of the Federal Reserve System, C&I Chargeoffs

3 This GMT to credit factor volatilities model is simplified and presented for illustrative purposes. Our ongoing climate research will focus on extending this approach to include a more formal statistical calibration.

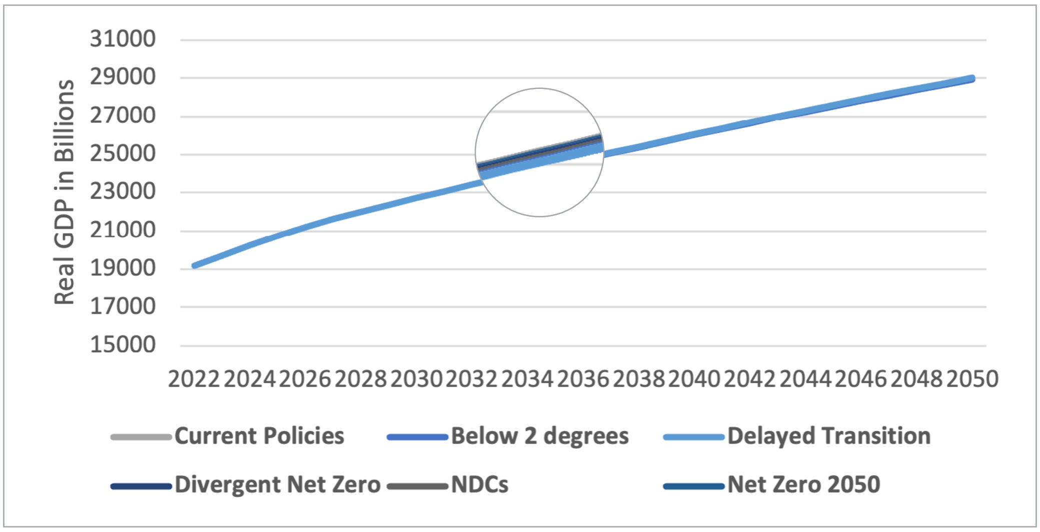

Figure 2: Real GDP Projections in NGFS Climate Scenarios
Source: NGFS

C. Adding Climate-Change Volatility Multipliers to Credit Models:

The discussion above suggests that, to affect credit losses, climate change must generate greater volatility in the factors driving credit risk. As briefly pointed out in the first paper, higher future climate driven volatility is expected in general and could be driven by a range of factors from; increasingly severe weather and physical damage, abrupt carbon policy changes, social and population migration and war 'tipping points' etc. So our application of aggregate volatility multipliers driven by projected GMT increases should ***be considered an aggregate measure of all of the future drivers of climate change.*** This allows us to illustrate the statistical impacts of future volatility on credit risk from the potential impact of climate and to also ***develop statistical probabilities attached to a given scenario.*** As a next step beyond the results presented in this second triptych paper it would be logical to build various assumptions and scenarios for ***differential volatility multipliers by specific industry sectors and regions.***

We introduce this into ZRE's IRMC model by applying climate-sensitive multipliers to the random, industry and region, Z shocks underlying credit risk. We express these multipliers as a function of global mean temperature (GMT). As GMT rises, the volatilities of shocks increase, contributing to a wider range of Z outcomes. The GMT varies across the different climate scenarios and this implies different, volatility multipliers (**Figure 3, Figure 4**). We calculate the climate-change, volatility multipliers (CMs) using the formula:

$CM_t = (1 + (GMTt - GMT_{2020})/14.5)^4$.

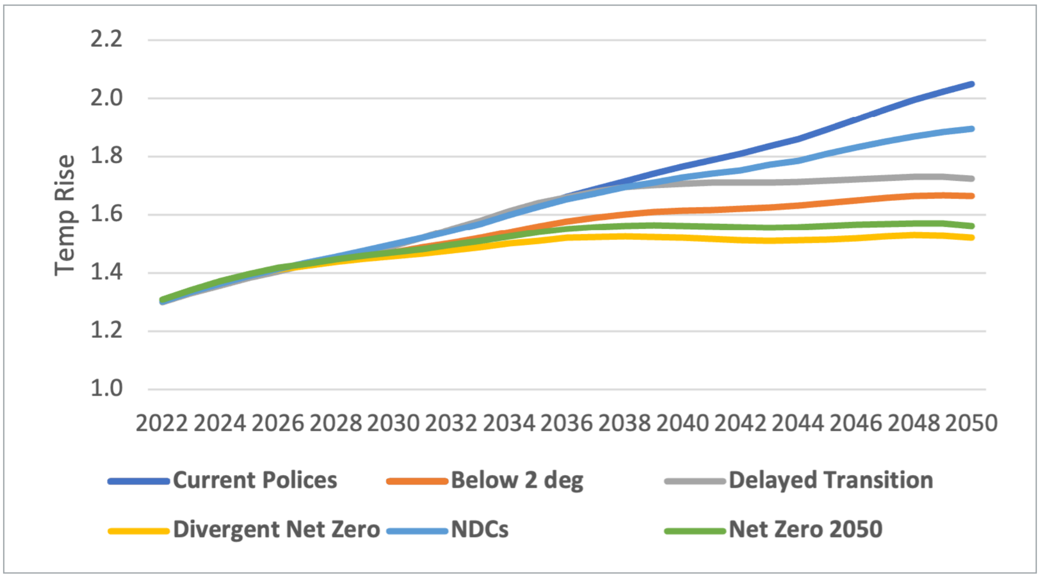

Figure 3: GMT Increases in NGFS Scenarios
Source: NGFS

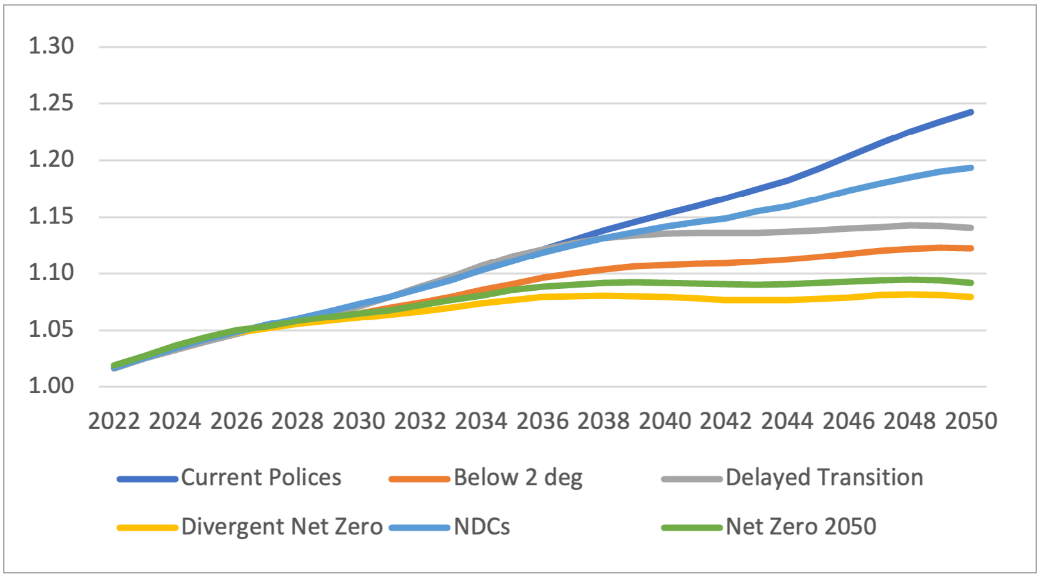

Figure 4: GMT-Implied Volatility Multipliers in NGFS Scenarios
Source: NGFS and Z-Risk Engine

Volatility Multipliers Produce Higher Credit Losses Related to Climate Change

Applying ZRE's, climate-sensitive, IRMC model, we've ***run 1,000, loss sims*** for a representative, C&I portfolio for each of the following climate scenarios: Baseline (no climate effects); NGFS Net Zero 2050; NGFS Delayed Transition; and NGFS Current Polices. For clarity, in the simulation results presented below, we only show three of the six NGFS scenarios shown in **Figures 3** and **4**. The Baseline involves no volatility multipliers, whereas the other three include the multipliers displayed above (**Figure 4**).

The results show that credit losses increase as climate change and the volatility multipliers rise more above one (**Table 1**). We also see that the climate effects become greater in the upper tail of the loss distribution. Thus, the expected credit losses for 2050 in the NGFS

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Net Zero 2050, NGFS Delayed Transition, and NGFS Current Policies scenarios rise relative to the baseline by 1.13x, 1.18x, and 1.34x, respectively. The 99th percentile losses in those scenarios rise relative to the baseline by 1.25x, 1.50x, and 1.67x, respectively.

For broad comparison purposes, the 2008/09 ***'Great Recession' produced a*** roughly ***2.3% realized credit loss rate for 2009 as measured by the FRB C&I index.*** For 2002, the realized credit loss rates were about 1.8% vs the 1990-22 average C&I credit loss rate from the FRB index of about 0.72%. Therefore these illustrative credit loss simulations using the hypothetical climate-to-volatility model coupled with the statistical industry-region credit factor model produce higher losses for all NGFS scenarios in the tail, 99% percentile.

Table 1: Estimated Credit Losses for Representative, US C&I Portfolio

	Credit Losses 2050						
	Relative to Limit				Relative to Baseline		
Statistic	No Climate Effects Baseline	NGFS Net Zero 2050	NGFS Delayed Transition	NGFS Current Policies	NGFS Net Zero 2050	NGFS Delayed Transition	NGFS Current Policies
99th Percentile	4.28%	5.34%	6.43%	7.16%	1.25	1.50	1.67
95th Percentile	1.88%	2.24%	2.39%	2.84%	1.19	1.27	1.51
Expected Value	0.60%	0.68%	0.71%	0.80%	1.13	1.18	1.34

Source: Z-Risk Engine analysis

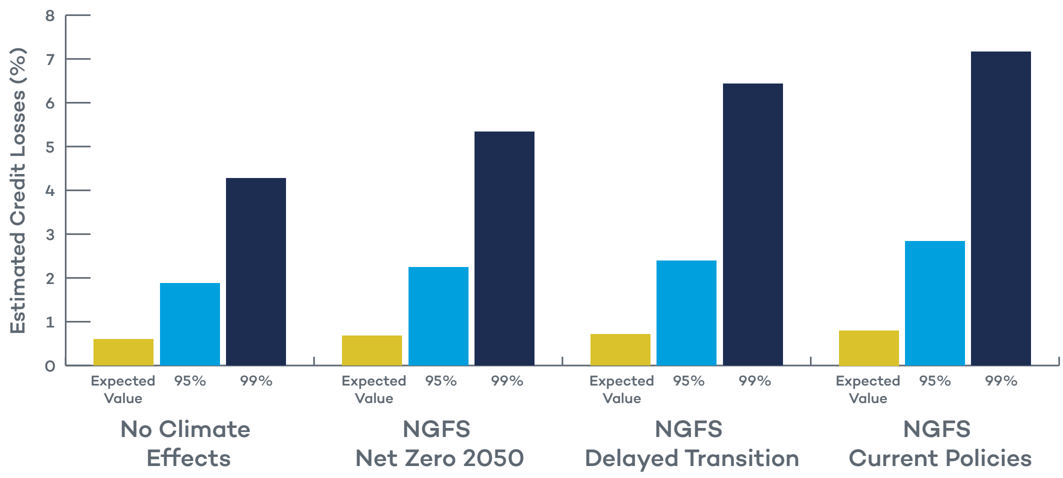

Figure 5: Estimated Credit Losses for Representative, US C&I Portfolio
Source: NGFS, Z-Risk Engine, C&I Illustrative US Portfolio as outlined in the Appendix.

In this paper, we've presented results for scenarios up to the year 2050. Note, however, that particularly in the NGFS Current Policies scenario, the GMT continues to rise up to more than 3 degrees above the pre-industrial mean value, implying credit losses considerably higher than those estimated for 2050 in these results. ZRE is also flexible and therefore can run scenarios over various time horizons for example up to the year 2100.

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As a final note, observe that the loss results presented below involve summing estimates for 20 distinct, US industries (**Figure 6**). While the exposure shares vary across sector to represent the approximate composition of US C&I loans, the TTC risk parameters of the facilities within each industry are the same. This simplifies the modeling, although some industries (i.e., banking) surely have below average, credit risk. Some industries have greater cyclical volatilities than others and this as well as the varying exposure shares accounts for the different amounts of expected loss by industry. ***If, as is possible, we were to introduce different TTC parameters or different climate multipliers by industry, this would also affect the industry composition of losses.***

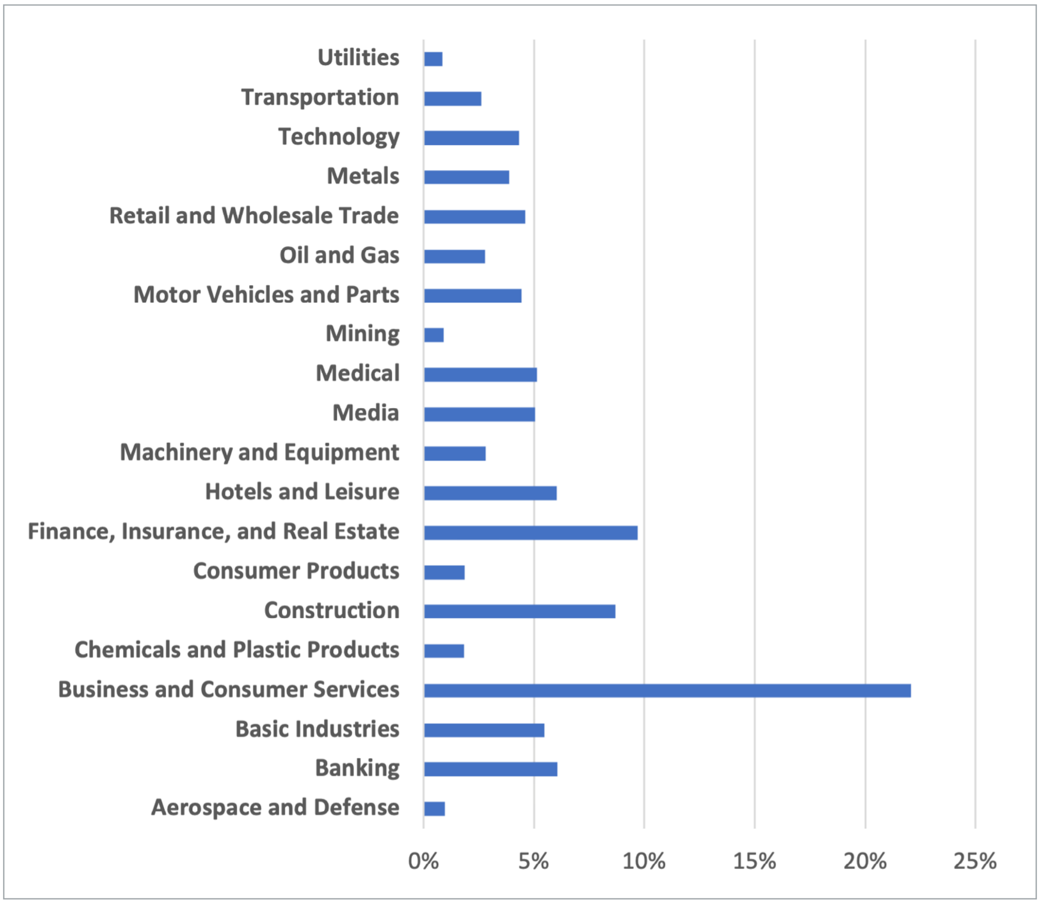

Figure 6: Industry Composition of 2050 Expected Losses in No-Climate-Effects Baseline
Source: Z-Risk Engine analysis

D. Future Research Needs to Seek a Calibration and Add Industry and Region Effects:

These estimates rely on the hypothetical climate-change multipliers, derived from the simple, illustrative GMT-to-Vol scaling and are not yet estimated empirically. This is the primary issue of a dearth in observed climate impact data at a more macro level that could support an empirical estimation of the GMT-volatility relationship. Enhancing this requires that in future research, analysts further explore calibrating this relationship. To obtain credible estimates of the effect of climate change on credit losses, one needs a formulation that is both theoretically plausible and has been found to be statistically reliable.

However, aside from this illustrative climate volatility scaling approach, the detailed ZRE credit factor models are empirically derived from 32 years of systematic credit risk observations. Therefore, this overall modelling approach provides a much richer assessment of potential future climate driven credit risk impacts. This includes the capability to assess climate credit risk uncertainties in substantially more detail than the current NGFS scenario approach.

Additionally, the above results come from a model with proportionately the same climate-change effects on volatility in every industry and region. Future work might introduce varying effects, with more climate-sensitive industries and regions having higher climate empirical volatility multipliers. In fact, customized scenarios from across the uncertainty spectrum with their related statistical significance could be developed from differential industry and region volatility assumptions.

III Summary:

The familiar NGFS climate-change scenarios show global warming as slowing economic growth rates, but not increasing the amplitude of economic cycles. As a result, climate change generally has limited effect on projected credit losses. This second triptych paper assumes, in contrast, that climate change increases the volatility of credit shocks as derived in the aggregate from a number of future risks related to rising GMTs. This assumption includes the presumption that climate change leads generally to more extreme weather as one driver of future risk. Not surprising, with climate change increasing the volatility of credit factors, we find that credit losses increase as global warming continues. Moreover, the largest impact occurs in severe recession scenarios.

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Appendix I: ZRE's Industry Region Monte Carlo (IRMC) Model

ZRE's IRMC ('Industry Region Monte Carlo') model:

- draws on randomly selected industry and region, Z shocks,
- enters those Z shocks into mean-reversion-momentum (MM) models of the stochastic evolution of industry and region Zs and thereby generates industry and region, Z sims,
- combines the industry and region Z sims into composite, industry-region ones,
- enters the industry-region, Z sims into PD, LGD, and EAD models for the facilities in a representative, C&I portfolio and thereby obtains MC sims for the related, defaults and credit losses.

In this study, the shocks driving the industry and region, Z sims have volatilities that rise as the climate warms as measured by the GMT. Thus, under more severe climate scenarios, the sims include more severe credit crises implying higher credit losses.

The industry and region Zs in this study derive from point-in-time (PIT) PDs estimated for a comprehensive set of listed companies across the world. In this study, we use Moody's CreditEdge EDFs for this purpose. We obtain industry and region, Z indexes by:

- transforming the monthly, listed-company EDFs into default-distance (DD) measures by applying the negative of the inverse-normal function,
- summarizing those DDs for selected, industries and regional grouping by taking medians,
- detrending the monthly median, DD series,
- forming DGAPs for each industry and region by expressing the detrended, monthly median DDs as deviations from long-run means, and
- dividing the DDGAPs for each industry or region by the standard deviation of annual changes in those DDGAPs.

Attributes of the Representative, C&I Portfolio:

The representative, C&I portfolio applied in the triptych papers includes a broad set of industries roughly representative of all, C&I loans (**Table 2**). Each industry-region Z index arise as a weighted average of a global industry, Z index and a regional, Z index. In the case of non-financial industries, the regional index in the combination includes only non-financial companies in its construction. In the case of financial industries, the regional index in the combination includes only financial companies. The weights involved in forming industry-region indexes derive from regressions of quarterly changes in DDs of listed companies within each industry on quarterly changes in the associated, industry and region, median DDs. Note that ZRE also creates an agriculture industry, but, in the Fed/OCC loan-loss data, agricultural loans are in a separate category outside of C&I. Thus, in this study, we exclude agricultural as a relevant industry.

Table 2: Industry Composition of the Representative C&I Portfolio

Weight	C&I Industry	Associated Region Grouping
1%	Aerospace and Defence	North America Corps
5%	Banking	North America FIs
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 FIs
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

Source: Z-Risk Engine analysis and assumptions.

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 3** 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 USA loss index, we apply only one region Z, for NA.

The $600 million portfolio, is then distributed to the five entity risk grades using the weights shown in **Table 3** and to the 20 industry sectors using the weights shown in **Table 2**. To simplify the model, we assume that the TTC attributes are fixed over time and are the same for every industry-region segment.

Table 3: TTC Risk Attributes of Facilities Within Each Industry-Region Grouping

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

Source: Z-Risk Engine analysis and assumptions.

Estimating Scenario Losses for Facilities in the Hypothetical Portfolio:
The quarterly scenario Zs enter into facility PD, LGD, and EAD models and thereby produce the quarterly estimates of losses. This See below for more detail.

Facility PDs:
In each scenario in each quarter for each facility in the representative portfolio, we apply a Probit PD model in deriving a quarterly PD. A Probit model uses a standard-normal, cumulative distribution function ('CDF') in transforming a DD measure into a PD. As applied here, the model has the following inputs: the quarterly, TTC PD transformed into a DD; the industry-region Z expressed relative to a normal Z consistent with the TTC PD; and various volatility parameters that convert the Z factor into a DD variation scaled for a quarterly model. The Z factor input together with the volatility parameters convert the TTC PD into a PIT one.

Facility LGDs:
The facility LGDs arise from a Tobit LGD model. This model has point masses at 0% and 100% and uses a normal CDF for the frequency of LGD outcomes above 0% and below 100%. In this study, the model has the following, facility inputs: TTC LGD; and the relevant, industry-region Z. The parameters of the model come from past, empirical results. We solve for the expected value of LGD, conditional on the scenario Z.

Facility EADs:
We use a CCF (Credit Conversion Factor) model sensitive to the credit cycle in deriving EADs for each facility in each scenario quarter. In such a model, the utilization in default rises above the performing facility's expected utilization rate by a proportion ('CCF') of the fraction unutilized under non-default conditions. The CCF in this study comes from a Probit model with the relevant, industry-region Z as an input. We scale the model so that, if Z is zero, the CCF equals the TTC value that appears as an attribute in the portfolio file. We've set the Z sensitivity of CCFs to that estimated in our past empirical work.

Facility and Portfolio, Conditional ECLs:
Each facility's expected credit loss ('ECL') in a scenario quarter derives as a product of the facility's, PD, expected LGD (ELGD) and expected EAD (EEAD) values for that quarter. The ECL and all of the component, expected values are conditional on the Z value in the quarter. We obtain the ECL for the C&I portfolio or various, sub-portfolios by summing the constituent, facility ECLs.

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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.

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