**CLIMATE CHANGE CREDIT RISK TRIPTYCH**[1]

# Paper Three: Climate Change Macro Volatility Effects Imply Higher Credit Losses

In this third climate triptych paper we assess a second set of climate change impacts on wholesale credit losses to 2050 alternatively using the Z-Risk Engine macro credit factor Monte Carlo simulation module. In doing so, we:

- Choose various NGFS GMT scenarios
- Calculate, for each GMT scenario, climate macro-volatility multipliers using an illustrative NGFS GMT-to-Volatility assumption
- Derive, through Monte Carlo simulation 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
- Obtain estimates of 99% tail losses somewhat smaller than those produced by the industry-region credit-factor model.

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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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## I. Overview – Triptych Paper Three:

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 third triptych paper, we apply the ZRE Macro Monte Carlo ('MMC') capability to assess the potential impact of increased climate volatility on future credit losses. The ZRE MMC approach assesses credit losses using MEV simulations as compared to paper two. 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 supports better understanding of key CST industry discussion points, including (1) use of an empirically founded climate credit risk approach, and (3) assessment of extreme climate scenarios including empirical assessment of 95% and 99% statistical confidence interval credit losses.

## II. Assessing Climate Change Macro Volatility Impacts on Wholesale Credit Losses:

### A. Introduction:

In the first two climate risk triptych papers, we've found that, for climate change to have an important effect on credit losses, it must increase the cyclical volatility of systematic, credit factors. Since the familiar, climate scenarios such as the NGFS ones show climate change as slowing growth, but not raising volatility, they imply that global warming generally has limited effect on credit losses.

In this third paper, we present a second set of estimates of climate change, volatility effects on credit losses. In paper two, we obtained such estimates from Z-Risk Engine's ('ZRE'), industry and region, Monte Carlo (IRMC) model. Here, we present estimates from ZRE's Macroeconomic Monte Carlo (MMC) model. The two models differ in that, applied to the US, IRMC traces credit losses to Z paths for 20 industry and two regional sectors (corporate and FIs) for the US corporate benchmark portfolio used in the studies. Whereas MMC traces them to Z paths for three, macroeconomic factors: stock prices, credit spreads, and GDP. The cyclical volatilities of the IRMC sims exceeds those of these MMC ones, and so the IRMC estimates of climate-change effects on credit losses exceed those presented here. However, applying the MMC model, we still find that more severe, climate scenarios imply higher credit losses especially in downturns, compared to the NGFS approach.

The quantitative results in this paper, like paper two, involve an assumed relationship between global mean temperatures (GMTs) and credit-factor volatilities. Thus far, we have no direct empirical results to substantiate this relationship between climate change and credit-factor volatilities. Thus, as in paper two, the quantitative results presented here remain hypothetical for the effects of climate and GMT. However, the overall model is statistical for the measurement of the empirical macro, industry and region credit factors.[2] In future analysis, we will explore further research in calibrating the climate credit factor volatility relationship.

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

As we've shown in these papers, 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 scenarios suggest that climate change has limited effect on credit losses.

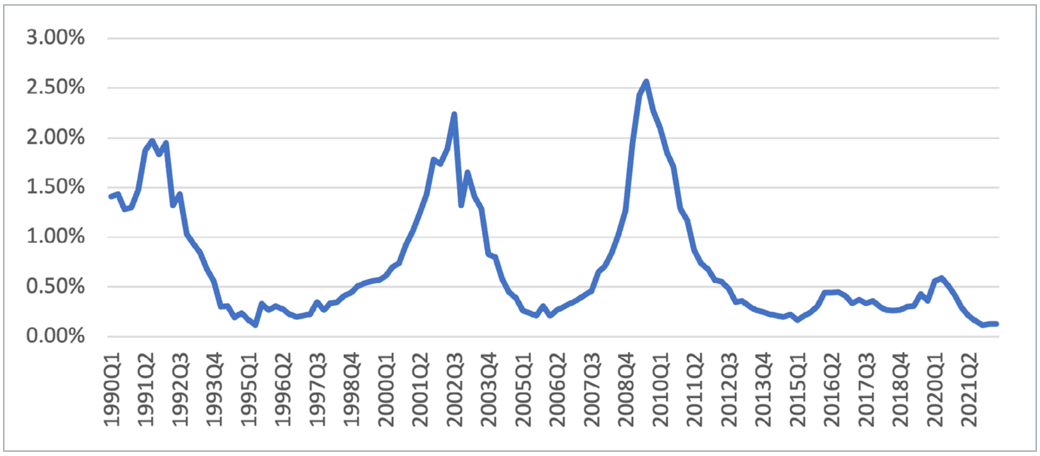



**Figure 1: Annualized Charge-Off Rates, US C&I Loans, Quarterly, Seasonally Adjusted**
*Source: Board of Governors of the Federal Reserve System*

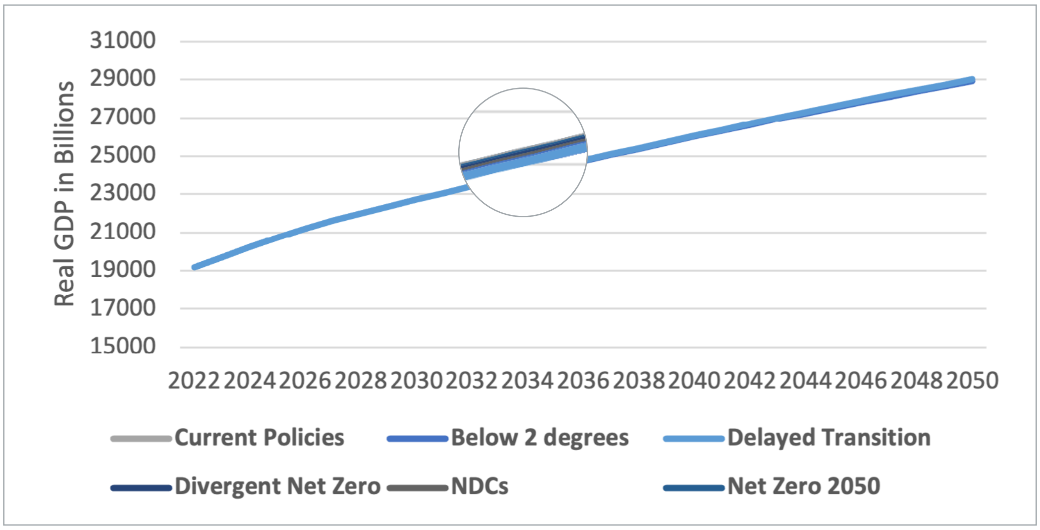



**Figure 2: Real GDP Projections in NGFS Climate Scenarios**
*Source: NGFS*

2 See Forest and Aguais, 2019, a, b, and c for the full ZRE specification and statistical validation of the macro, Industry and region factor models.

## C. Adding Climate-Change Macro 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 volatility which are translated to the systematic credit factors.

In paper two we introduced greater volatility through multipliers applied to industry and region simulations. Here, alternatively, we introduce volatility into ZRE's MMC model by applying climate-sensitive multipliers to the random, Macro-Z shocks underlying credit risk. We also apply the multipliers to industry and region errors representing the random deviations of industry and region Zs from the values expected on the basis of the macro factors.[3] 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:

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

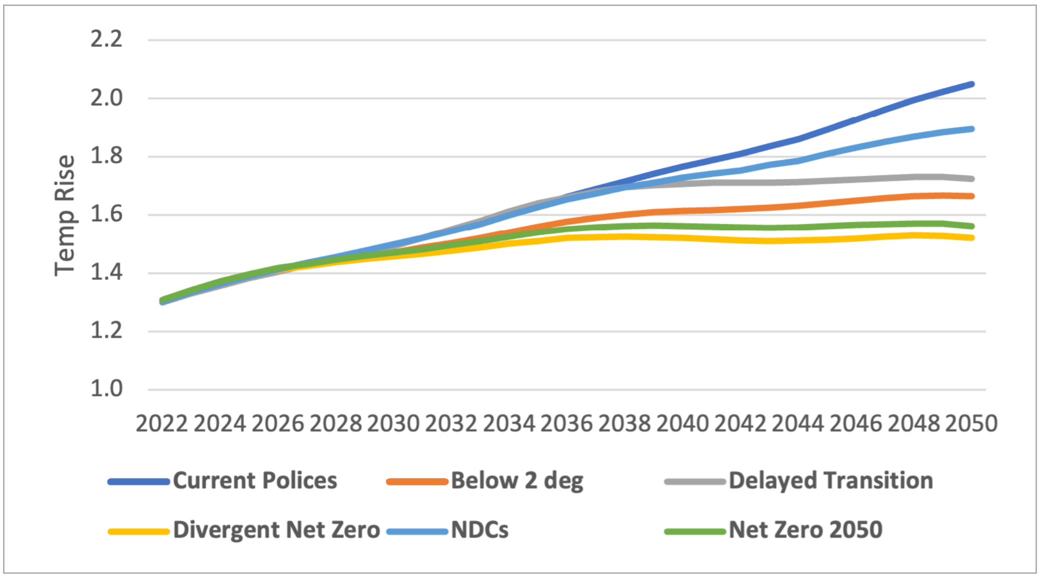



**Figure 3: GMT Increases in NGFS Scenarios**
*Source: NGFS*

3 See forest and Aguais (2019 b) for the full specification and application of the macro factor model using regulatory stress CCAR scenarios.

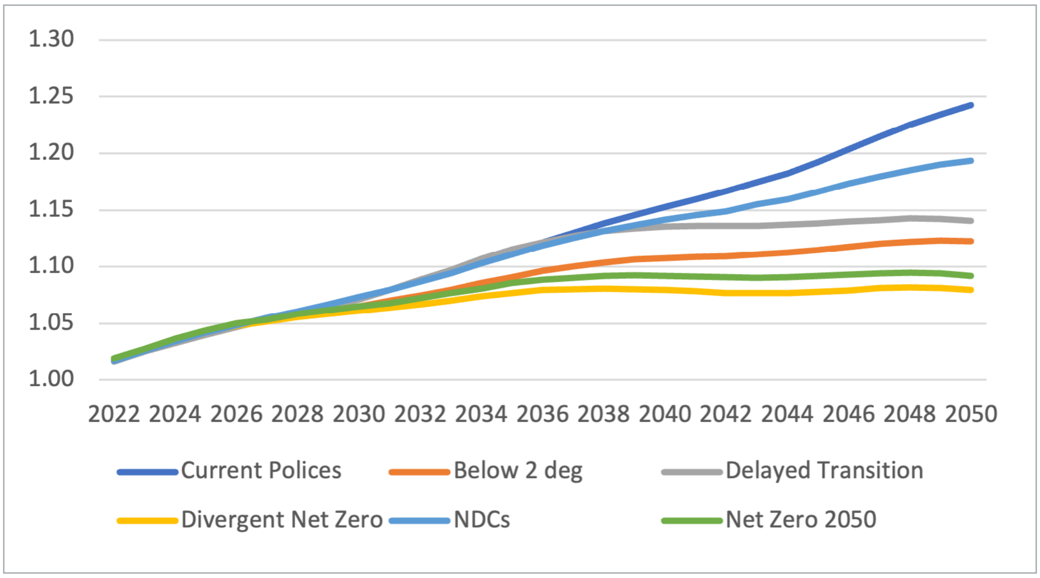



**Figure 4: GMT-Implied Volatility Multipliers in NGFS Scenarios**
*Source: NGFS and Z-Risk Engine analysis*

### Macro Z Volatility Multipliers Produce Higher Credit Losses Related to Climate Change

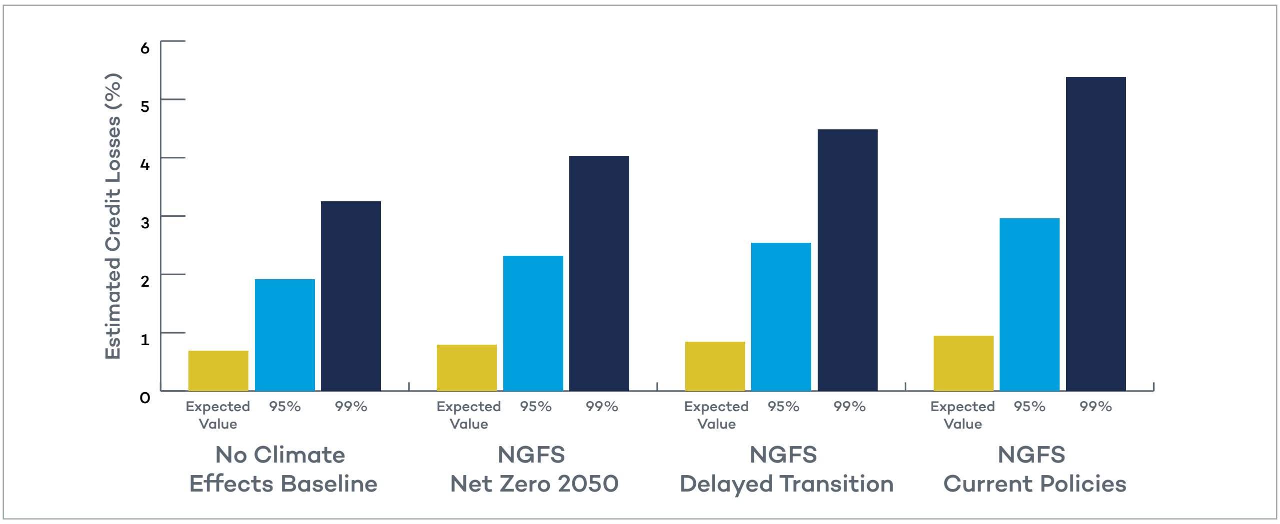
Applying ZRE's, adapted climate sensitive, MMC model, we've ***run 1,000, loss sims*** for a representative, C&I portfolio for each of the following climate scenarios: Baseline (no climate effects); NGFS Net Zero 2050; NGFS Delayed Transition; and NGFS Current Polices. For clarity, in the simulation 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 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 in the NGFS Net Zero 2050, NGFS Delayed Transition, and NGFS Current Policies scenarios rise relative to the baseline by 1.14x. 1.22x, and 1.37x, respectively. The 99th percentile losses in those scenarios rise relative to the baseline by 1.24x. 1.38x, and 1.65x, respectively.

**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 | 3.25% | 4.03% | 4.48% | 5.38% | 1.24 | 1.38 | 1.65 |
| 95th Percentile | 1.91% | 2.32% | 2.54% | 2.96% | 1.21 | 1.33 | 1.55 |
| Expected Value | 0.69% | 0.79% | 0.84% | 0.95% | 1.14 | 1.22 | 1.37 |

*Source: NGFS and Z-Risk Engine analysis*




*Source: NGFS and Z-Risk Engine analysis*

In this paper, we've presented results for scenarios, driven by MEV volatility 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.

In triptych paper two, we applied ZRE's industry-region, Monte Carlo (IRMC) model in estimating credit losses on the same, representative, C&I portfolio used in all three papers. Paper two applied volatility multipliers derived from the hypothetical GMT model using IRMC to apply industry region statistical shocks. Here in paper three, we apply statistical shocks alternatively, using the MMC model. In both cases, the results indicate that climate-change effects on volatility produce higher credit losses. However, the numerical estimates are somewhat different between the two approaches.

The estimated expected and 95th percentile losses in paper two, are slightly below those presented here, whereas the 99th percentile, credit losses are higher. The MMC model here yields lower estimates of extreme (greater than 95th percentile) losses, because the volatility of the credit-factor projections are lower when one derives industry and region shocks indirectly from the three, macro factors we simulate here, GDP, credit spreads and equity prices. Whereas under both approaches, the loss volatilities increase as the climate scenario becomes more severe, the volatilities are somewhat lower overall under the MMC model (**Figure 5**).

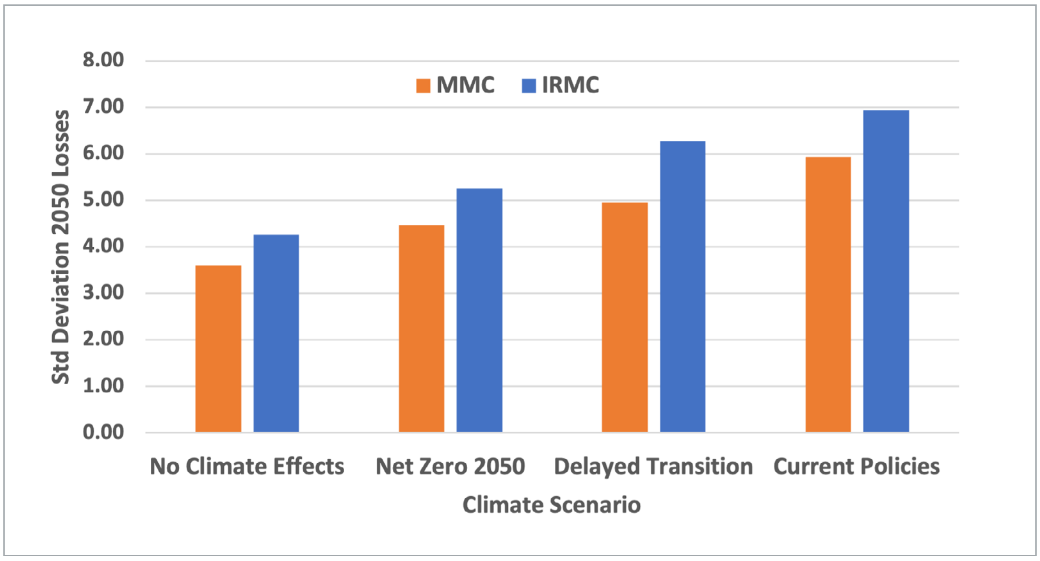



**Figure 5: C&I Loss Volatilities Under Alternate Climate Scenarios from Two Models**
*Source: NGFS and Z-Risk Engine analysis*

## Future Research Needs to Seek a Calibration and Add Climate Driven Industry and Region Effects

These estimates rely on hypothetical climate-change multipliers, whether applied to industry region or macro credit factors, that are themselves not yet estimated from an empirical model. However, this hypothetical GMT model is applied to a well-founded, empirical credit factor model for the macro, and, industry and region factors. In our future research, we will explore calibrating the climate credit volatility relationship. To obtain credible estimates of the effect of climate change on credit losses, one needs a formulation of the climate impact that is both theoretically plausible and has been found to have reasonable statistical reliability.[4]

4 This further research on calibrating the GMT-to-volatility relationship is dependent as pointed out in paper one on deriving an empirical relationship from the limited roughly 50 years of climate impacts in the data. However, as the overall credit factor model is quite robust, having been estimated from detailed EDF data for the three previous recessions, so the detailed credit factor model utilized here provides a strong statistical foundation to build on.

## III. Summary: Three Climate Triptych Papers

In climate triptych papers one and two, we found that, for climate change to produce larger, unexpected declines in asset values and cash flows and thereby higher credit losses, it must increase the cyclical volatility of systematic, credit factors. Since the familiar, climate scenarios such as the NGFS ones show climate change as slowing growth, but not increasing cyclicality, they imply that global warming has very little effect on systematic credit losses generally.

In this third triptych paper, we present a second set of estimates of climate-change, volatility effects on credit losses to compare with those in paper two. Here, we consider climate change as increasing the volatilities of a few, macroeconomic, credit factors, with effects distributed across industries and regions. In paper two, in contrast, we view the volatility increases as occurring directly within the industries and regions. The paper two model uses industry/region simulations and this third paper uses macroeconomic driver simulations, with both broadly producing similar results. However, the macro-simulation model presented here yields moderately higher values for expected losses whereas the industry/region model in paper two produces higher values for losses in the upper tail (> 95th percentile) of the loss distribution. ***In both cases, we find that more severe climate scenarios generally imply higher volatility and therefore higher credit losses.***

The various regulatory and other studies to-date have attempted to quantify the credit impacts of the application of the top-down NGFS scenarios in various ways, focusing more effort on physical risk and the effects of carbon policy combined with carbon emissions data. Those climate stress test efforts seek to drive firm-level climate impacts from aggregate scenarios. These regulatory approaches have not usually included the application of a more detailed credit factor model that assesses detailed systematic cyclical credit risk volatility.

In broad terms, in contrast to other climate stress test studies our focus here seeks to add a more formal statistical foundation to CST by focusing on the systematic credit risk drivers that have been calibrated to detailed, observed credit risk volatility over the last three recessions. These models use Credit Edge EDF data from 1990 onwards to assess industry and region systematic credit risk.

The approach here, as has been pointed out, has a stronger, statistical credit risk foundation, but is for the moment driven by the simplified, illustrative GMT-to-volatility overall assumption. Our continuing climate research will focus on seeking to find a better statistical foundation for this GMT-volatility model and assess potential volatility differences in individual industry and region factors instead of applying the same volatility assumption across all industries and regions.

In addition, to the further research points discussed above, the systematic credit risk approach presented here can be ***potentially complementary*** to current CST research focused on short run physical risks and more broadly on the longer-run carbon transition aspects of climate change.



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## Appendix: ZRE's Macro Monte Carlo (MMC) Model:

**ZRE's US MMC model:**

- draws on randomly selected shocks to macroeconomic (Macro) Z indices derived from US data on equity prices ('ZE'), Baa spreads ('ZS'), and GDP ('ZG'),
- puts those shocks into mean-reversion-momentum (MM) models of the stochastic evolution of the Macro-Z indices and thereby generates joint, ZE, ZS, and ZG sims,
- places those Macro-Z sims into a model that bridges from Macro to industry and region Zs and thereby obtains the related, 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 ZE (equities) series in this study:**

- starts with the Wilshire 5000, stock-price index,
- forms the ratio of that index to an autoregressive-first-order (AR1) moving average of the index,
- converts that ratio to a default-distance ('DD') measure by taking the natural logarithm of a scaling factor times one plus the ratio ( $DD = ln(f * (1 + \text{ratio}))$),
- obtains a DDGAP series by subtracting the 1990-to-date average value of the DDs,
- transforms the DDGAPs into Zs by dividing by the standard deviation of 1990-to-date, annual changes in DDGAPs.

**The ZS (credit spreads) series:**

- starts with the US, Baa, credit-spread index,
- converts the spreads to DDs by dividing by 0.6 and applying the negative of the inverse-normal function ( $DD = -\Phi^{-1}(spread/0.6)$),
- obtains a DDGAP series by subtracting the 1990-to-date average value of the DDs,
- transforms the DDGAPs into Zs by dividing by the standard deviation of 1990-to-date, annual changes in DDGAPs.

**The ZG (GDP) series:**

- starts with the US GDP, time series,
- forms the ratio of that series to an autoregressive-first-order (AR1) moving average of the series,
- converts that ratio to a default-distance ('DD') measure by taking the natural logarithm of a scaling factor times one plus the ratio ( $DD = ln(f * (1 + \text{ratio}))$),
- obtains a DDGAP series by subtracting the 1990-to-date average value of the DDs,
- transforms the DDGAPs into Zs by dividing by the standard deviation of 1990-to-date, annual changes in DDGAPs.

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 all three studies 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 PDTTC | LGDTTC | CCFTTC | 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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