CLIMATE CHANGE CREDIT RISK TRIPTYCH[1]

Paper One: Smooth NGFS Climate Scenarios Imply Minimal Impacts on Corporate Credit Losses

To support long-run banking system viability from a Macro-Prudential point of view, climate related credit risk is a key discussion point driving current climate stress test R&D. Led by regulators and the NGFS, early modelling approaches utilize 'smooth', top-down scenarios coupled with carbon emissions data to assess future climate related credit losses for individual firms. While the NGFS approach is in its infancy, industry feedback has identified a number of discussion points with using top-down scenarios that may not fully reflect the potential for a broader range of more extreme future climate impacts. Additionally, the use of empirical models of detailed credit risk with dedicated industry and region models could improve on the current use of top-down distributed aggregate economic measures.

In contrast to the NGFS approach, credit risks are generally not driven by smooth macro-economic trends but by ***unexpected economic shocks*** that represent higher ***volatility and systematic deviations from average trends*** as seen in the three most recent recessions. Therefore a key contribution to current approaches for assessing future climate induced credit risks could assess systematic volatility in addition to trends in economic variables.

These triptych papers explore future climate induced credit risk and credit risk volatility under three different empirical assessments. To conduct these empirical estimates we utilize a well-known, multi-factor credit portfolio model implemented in the Z-Risk Engine. In each case expected and tail credit losses are assessed up through 2050 using a benchmark US C&I credit portfolio.

The first assessment of climate related credit losses compares NGFS climate scenarios with a CCAR severely adverse scenario to suggest that ***volatility not trends ultimately drives credit risk***. For the second and third climate credit risk assessments we use NGFS GMT projections to estimate volatility effects on climate induced credit losses. These assessments use both industry and region and macro-economic factor model simulations. These three empirical assessments respond to key industry points currently under discussion and provide an additional, complementary foundation for assessing climate driven credit risks, highlighting the role of systematic credit volatility as compared to the NGFS approach focused on macro-economic trends.

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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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I. Introduction To Three Climate Risk Triptych Papers:

Due to recent increased concerns over the long-term effects of climate change, regulators in several jurisdictions have worked with banks to assess climate stress tests ('CST') for both the possible effects of climate change on their clients and the financial losses that a bank might incur as a consequence to those effects. Some regulators notably the ECB working with the NGFS consortium have proposed that banks try to identify the credit losses associated with a range of 'top-down' style scenarios involving varying amounts of mitigation and climate-change intensities.

These NGFS scenarios differ only in minor ways with respect to trend rates of economic growth. The trend variations related to differing amounts of costly mitigation and adaptation provide some basis for cost-benefit analysis of different climate-change policies. But the related, economic NGFS projections involve no sharp deviations downward from trend GDP growth and thus the different scenarios look quite similar in terms of credit-risk drivers. Consequently, the existing NGFS scenarios provide only a limited basis for assessing climate-change impacts on credit risk.

Credit risk is generally not driven by smooth macro-economic trends but by ***unexpected economic shocks*** that ***represent systematic deviations from longer-run average trends***. As examples, the last three global recessions have seen credit losses spike unexpectedly to about 3X their long run average level of credit losses. Therefore, any assessment of future climate induced credit risks must assess systematic volatility not just trends in economic variables such as GDP. Luckily there is substantial objective and empirical evidence available and a framework to assess credit risk volatility that can provide a complementary foundation to early CST approaches.

For clarity, our focus is on assessing climate change primarily in relation to aggregate systematic credit risk volatility. Therefore, we don't directly assess climate impacts of individual influences such as, carbon emissions, carbon mitigation, and firm-level physical risks. We see assessment of these more specific climate impacts as complementary to what we present here, and that the systematic volatility approach encompasses in the aggregate a range of climate factors. The climate approach presented provides a stronger empirical foundation for detailed assessment of systematic credit risk, and is complementary to other developing aspects of modelling climate change. Further extensions to the assessments will also be part of our CST agenda.

Developing and implementing a more detailed credit risk foundation for climate analysis – especially using dedicated statistical industry sector and region credit factor models potentially complements the current NGFS scenario-based approach. These climate triptych papers are written therefore, to contribute to the early development of climate stress test approaches and the overall industry discussion and debate.

The climate triptych papers outlined below explore these points, using the Z-Risk Engine ('ZRE') portfolio solution to produce three different empirical analyses of climate change impacts on credit risk.[2] This first paper compares the NGFS scenarios with the CCAR

2 The Z-Risk Engine solution developed over the last 15 years in multiple large banks, applies a detailed multi-factor credit approach modeling systematic credit cycles to estimate full Point-in-Time credit measures derived bank's IRB credit models. ZRE is used to support IFRS9 and stress testing for wholesale banking portfolios. The ZRE solution is calibrated to public-firm default models to develop the factor models. For our core research papers, see Belkin (1998 a, b) and Forest and Aguais (2019, a, b c). These research publications and our other, substantial PIT/TTC credit model publications are all available at; www.z-riskengine.com.

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(Capital Stress) ones produced by the US Federal Reserve.[3] The CCAR, baseline and Severely Adverse ('SA') scenarios involve sharply different economic outlooks. The baseline one assumes smooth growth and the SA one assumes a deep recession. Consequently, the credit losses are much higher in the SA scenario. In contrast, the NGFS scenarios are uniformly smooth, without cycles, and so they indicate that varying amounts of climate change have very limited effect on credit losses. All of the NGFS scenarios look broadly similar to the baseline CCAR scenario.

The second and third triptych papers introduce into the ZRE industry and region, credit-cycle models a relationship between climate change and credit-factor volatilities. We apply a climate-sensitive volatility model in estimating losses incurred by a representative, US, Commercial and Industrial (C&I) loan portfolio, showing that credit losses rise as climate change becomes more severe, with increasing general volatility. The second and third papers demonstrate these impacts using two, different Z-Risk Engine (ZRE) models. Paper two utilizes the ZRE industry region factor model to simulate the effect of higher volatility while paper three simulates the MEV drivers of the industry and region factors.

Climate Stress Testing Requires an Enhanced Empirical Credit Risk Foundation

The empirical climate assessments presented here are grounded in a well specified multi-factor credit risk framework to contribute to the overall industry CST debate by proposing a more solid systematic credit risk foundation. Given the huge level of future climate uncertainty overall and the narrower focus of current scenario-based approaches, the foundational systematic credit risk results presented here also provide a statistical approach for assessing climate uncertainty.

Setting a stronger empirical credit risk foundational approach then allows for climate emissions data and future carbon policy and the 'green' energy 'revolution' to be further integrated with this systematic credit factor foundation. Therefore, the research and empirical assessments presented in these papers are written to contribute to the development of a broader overall 'framework' for CST, complementing current NGFS approaches.

The ZRE multi-factor modelling approach has been developed over many years to support development of more accurate, market-based Point-in-Time ('PIT') credit measures and is calibrated for the purposes of these triptych papers to 32 years (1990-22) of Moody's CreditEdge EDFs covering roughly 37k public companies.[4] [5] CreditEdge represents probably the best credit risk data set available for calibrating systematic credit risk factor models.[6] [7]

3 For clarity, the time horizon for CCAR scenarios is 'short-run' and the NGFS scenarios are usually applied to longer-run horizons. The comparison we make focuses on the effects of systematic factors not the time horizon differences.

4 The ZRE approach was originally developed to support the Basel II Waivers of Barclays Capital and Royal Bank of Scotland, and a recent joint Case Study presents the details of a ZRE implementation at DBS Bank in Singapore, see bibliography.

5 Moody's CreditEdge software provides Expected Default Frequencies ('EDFs') for all publicly traded companies globally.

6 We use EDFs in our research presented here but ZRE can be calibrated to any market-based, public-firm default model.

7 The EDF approach utilizes market-based information to assess credit risks for individual firms as stemming from a combination of asset value volatility and debt leverage for each publicly traded company. We aggregate the individual company EDFs to create the systematic credit cycle indices applied in ZRE.

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Current CST Approaches: Summarizing Key Industry Feedback and Discussion Points

In current CST modelling, early approaches are primarily 'top-down', derived from CO2-driven temperature projections and IAMs ('Independent Assessment Models') focused on aggregate and regional GDP and in some cases carbon prices. The usual approach runs standardized deterministic 'top-down' scenarios developed by the NGFS global consortium. NGFS scenarios are becoming widely used and therefore provide the benefit of broadly supporting industry consistency. They also provide key contributions to early CST R&D.

However, recent industry debate and feedback have expressed a set of general discussion points related to applying primarily scenario-based approaches for CST, including:

1. Use of ***deterministic scenarios*** that are based on quite ***limited objective, empirical data***,
2. Application of IAM-derived mostly 'smooth trend-like' scenarios – which are not the usual drivers of ***systematic credit risk***, which is usually driven by ***volatility and unexpected economic shocks***,
3. Lack of incorporation of more ***extreme near-catastrophic future 'states of the world'***, which limits NGFS assessment of extreme climate risks,
4. 'Top down' approaches (IAM) support only a ***limited ability to assess granular risk*** effectively as this approach usually cannot assess industry and financial sector behaviour in detail, and,
5. Developing ***more detailed narratives*** on potential climate extremes could provide further economic logic for a wider range of potential scenarios.

Future climate risk impacts are highly uncertain and assessing future credit risks over long 30-year or more horizons is a quite complicated task. It's not surprizing that a number of different ideas concerning CST approaches are currently under discussion in the industry. The current CST NGFS scenario-focus generally seems to stem from the lack of, measurable, historical climate impacts on detailed economic, financial and industry sector data. Therefore, the NGFS has developed 'stylised' scenarios derived from simplified 'top-down' models. Thus, the current historical climate data situation substantially limits the ability to better assess climate uncertainty and develop more empirical, statistical analysis including assessing implied probabilities of extreme climate scenarios. Based on this it's not surprising the general NGFS approach has been developed based upon scenarios, which is consistent with traditional stress testing.

The purpose of these climate triptych papers is to consider in turn each of these key CST industry discussion points in the context of the empirical credit risk assessments we present.

This first climate triptych paper follows the outline below:

- **Section II** briefly summarises industry feedback and CST discussion points,
- **Section III** assesses NGFS scenarios vs a CCAR stress scenario demonstrating that trend-like NGFS scenarios predict minimal systematic credit risk impacts in contrast to CCAR stress scenarios,
- **Section IV** provides a summary,
- **Appendix I** provides additional summary notes on the assumptions used in the ZRE empirical analysis presented in Section II, and,
- **Appendix II** provides summary back-testing results for the ZRE approach.

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II. Review of Current CST Industry Discussion Points:

In this section we review the primary industry feedback and discussion points related to current CST model development.

NGFS: The Primary Approach to CST

CST research is primarily driven by a set of NGFS standardised future climate scenarios, see Boirard et al (2022) and Monasterolo (2022), for a general discussion, and NGFS (2022). These models are primarily top-down and motivated generally by very high levels of future uncertainty and a lack of historical data available to build detailed empirical, predictive CST models. As pointed out in Aguais (2022), using the Rumsfeld risk taxonomy, climate risk is usually thought of as a 'known unknown'. What is 'known' is that broad measures of global temperature (driven by CO2 levels) most likely will increase and climate change policy responses have the potential to substantially impact carbon usage (carbon asset stranding) and economic and financial activity globally (GDP). Increasing severe weather volatility creating physical climate risk is already happening relatively often.

What is 'unknown' is how much these broad measures of potential temperature change and atmospheric CO2 will impact GDP globally, economic activity generally and its volatility, and society overall. Future carbon policy in the form of carbon pricing primarily and future technology changes in energy markets also contribute to future climate uncertainty. On a historical basis, climate change has only been observed over the last roughly 50 years. For example, an 'unofficial date' for the beginning of climate change impacts has been dated nominally to, 1976 see, Flannery, (2005). Therefore, climate change is fundamentally embedded in the last roughly 50 years of observed economic and financial data – but detailed statistical measures of climate impacts are hard to extract.

Narrower physical climate trend impacts through measured CO2 emissions, rising global mean temperatures and increasing severe weather volatility are generally observable. However, empirical links between temperature changes, climate impacts, GDP, and more detailed sector impacts and therefore credit risk are extremely hard to establish on a systematic statistical basis. The problem is credit risk in principle is driven by unexpected economic shocks not trend variables like mean temperature and CO2 levels. In addition to substantial uncertainty, climate risk is also assessed to have 'fat tails', see Wagner and Weitzman (2015).

Scenario-Based Approaches Focus on 'Stylised' Scenarios Because Future Climate Change Impacts Are Highly Uncertain

Scenario-based approaches however have their own limitations, as they are ultimately hard to validate because they basically represent 'what if' deterministic views of possible future states of the world, see Hughes (2021 a, b). CST approaches like the one under development for example at the ECB, see ECB (2021) are also driven top-down so these types of IAM-style models equally have a hard time assessing disaggregated sectors

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in detail, see Pitman et al (2022).[8 9] 'We conclude 'top-down' approaches are likely to be flawed when applied at a granular scale.... most fundamental, uncertainty associated with projections of future climate extremes must be propagated through to estimating risk.... we strongly encourage a review of top-down approaches before they become the de facto standards...'.[10 11]

Current CST approaches not only have a hard time 'distributing climate risk' to lower levels -- as has been pointed out in Aguais (2022) and Cliffe (2021) – in addition, Kemp et al (2022) also states; 'prudent risk management requires consideration of bad-to-worse-case scenarios...for climate change, such potential futures are poorly understood... could anthropogenic climate change result in worldwide societal collapse or even human extinction?'.[12] To better represent the substantial range of future climate 'states of the world' relative to the narrower scenarios embedded in current regulatory CST, enhanced models require better ways to capture 'critical triggers, tipping points [cascading, correlated risks] and interdependence between the climate, [industry sectors and regions], the economy, politics, finance and technology'.[13]

The recent Real World Climate Scenarios ('RWCS', 2022) roundtable has elaborated on some of these concerns suggesting that better and more detailed 'climate narratives' should be part of enhanced CST approaches. [14] Adding more extreme, complex long-run climate scenarios are key to developing a more unbiased 'candidate set of future CST outcomes'. ***Risk modelling*** in general is about ***assessing an unbiased range of potential future outcomes*** and ***estimating*** (as best as possible) ***related empirical probabilities***. Current CST approaches while making progress, seem to ***lack both of these aspects inherent in general risk prediction models***.

Khanna (2022) has recently asked, 'What Comes After the Coming Climate Anarchy?' suggesting potential extreme scenarios could have substantially negative impacts. David Wallace-Wells highlighted potential long-run existential concerns at plus 6 degrees C or more in the Uninhabitable Earth (2015). Kemp et al (2022) also express substantial

8 There is an entire literature discussing the pros and cons of using IAM-style models to drive CST approaches, which we exclude from this brief discussion of industry concerns. See Asefi-Najafabady (2021) and Monasterolo (2022) for a more detailed discussion of IAM-style models generally.

9 CST approaches like the one under development at the ECB, complement the top-down NGFS scenarios with disaggregated variables linked to a large sample of European-wide commercial firms (roughly 2-3 million) including geo-location data to assess firm-level credit risks. However, this approach is still primarily driven top-down.

10 See Pitman et al (2022) page 1.

11 Concerns with more 'top-down' model approaches not successfully capturing lower-level, sectoral variation is just as relevant for projecting expected credit losses under IFRS9 or CECL. Nearly all banks currently use a combination of their IRB credit models regressed on macro-economic variables (MEV). Using just MEVs in general to predict systematic changes in credit risk for IFRS9 does not fully capture the PIT credit risk variability observed at the industry sector and region level during the last 3 recessions.

12 See Kemp et al (2022) page 1.

13 See Cliffe (2021) brackets have been added to the author's quotes.

14 Adding climate narratives given substantial uncertainty is a positive suggestion and seems to stem directly with frustration with the use of 'stylized' NGFS scenarios. We agree with these points but also suggest a more solid objective and statistical foundation for assessing systematic climate risk, as presented in these triptych papers is also a key part of a more 'holistic' CST framework.

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concerns about the lack of inclusion of catastrophic scenarios, stating: 'climate catastrophe is relatively under-studied and poorly understood…cascading impacts are underexamined'.[15]

The ultimate existential metaphor for the potential impact of climate change was developed in the 2021 Paramount film, 'Don't Look Up' – we call this the 'DiCaprio Scenario'. Overall, building on early CST work requires a much 'broader' range of possible future risks – however, as Stern and Stiglitz suggest (2022) including a 'DiCaprio Scenario' for the end of the world would usually make CST models intractable.

Scenario Approaches Lack Empirically Based Measures of Credit Risk Volatility

Currently climate change impacts are assessed as stemming from physical and transition risks over both short and long-run time horizons, with the focus of current CST efforts focused primarily on credit risk.[16] To a certain extent given currently observed severe weather changes, research on short-run climate risks focuses somewhat more on physical risks while the regulatory driven CST research utilises long-run horizons and seeks to assess both physical and transition risk together.

Focusing on current CST research and the use of smooth, 'stylized' NGFS scenarios a key question to ask is whether these types of approaches can capture credit risk generally which is usually driven by unexpected economic shocks or volatility in underlying systematic economic variables.[17] The preliminary empirical results from current approaches for assessing long-run climate credit risks suggests the aggregate impacts on banks doesn't generally threaten the overall stability of the banking system.[18] Therefore, a ***key objective of this first triptych paper is to compare NGFS and CCAR scenarios*** to demonstrate that more limited credit risk impacts stem partly from applying smooth, trend-like scenarios.

Carbon asset stranding generally, and the application of emissions data is currently used in most CST approaches to assess individual companies and industry risks inherent in the application of a formal, future carbon policy. Assessing these risks in the near-to-longer term are valid objectives. However, in more extreme cataclysmic narratives as Khanna points out, famine, major population migration, war, de-urbanization, global drought, etc are potentially larger drivers of future climate chaos. Therefore, CST will need to further ***evolve to broaden the breadth of potential future states of the world*** well beyond the narrower focus primarily on weather-related physical risks and carbon transition.

15 See Kemp et al (2022) page 1.

16 The narrower focus on credit risk is driven primarily by the Macro-Prudential objectives of financial regulators. Future climate risks in totality ultimately encompass market and operational risks plus broader social and political risks. Consistent with the CST literature and the narrower objectives of regulators our focus in the triptych papers is on credit risk.

17 Since 1990 there have been 3 recessions generally on a global basis, that produced a roughly 3X increase in measured Point-in-Time ('PIT') credit losses and default rates ('DRs') as compared to long-run average Through-the-Cycle ('TTC') credit losses. In all three of these credit cycle events; unexpected shocks were the main driver of substantial credit risk increases. This is the reason short-run capital stress tests such as CCAR focus on unexpected economic shocks to assess banking capital adequacy.

18 To-date several CST analyses primarily by regulators, have sought to estimate climate-induced increases in credit risks in banks. Without reviewing these results in detail, most seem to suggest these impacts aren't substantial and are generally predicted to be less than the credit risk impacts stemming from the 'Great Recession'.

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Overall, we have highlighted some of the key discussion points discussed in the literature in relation to current CST efforts. This brief review of current discussion points helps set the context for the empirical climate analysis presented in these climate triptych papers. ZRE is used to provide a solid empirical, objective assessment of systematic credit risks by industry and region supporting better understanding of discussion points (1) and (4) that suggest a better sectoral and empirical CST foundation is required. ZRE is applied in this first triptych paper to assess discussion point (2) on the role of unexpected economic shocks in predicting systematic credit risk vs NGFS scenarios. Triptych papers two and three deal with credit factor simulations and future climate volatility increases to help inform discussion point (3) on the lack of more extreme scenario outcomes.

The idea of applying multi-factor simulation-based approaches to climate risk isn't completely new as earlier this year, Garnier et al (2022) have proposed using an approach similar to the ZRE approach we have been developing for the last 15 years. However, we have a production version of ZRE currently implemented that is estimated from long-run Moody's CreditEdge EDF data for 1990-22. The empirical climate research presented in the climate triptych papers therefore, provides a ***solid empirical starting point for assessing credit risks driven by climate uncertainty***.

The overall logic of this analysis is that future economic shocks, rising weather severity and increasing physical climate damage, 'tipping points' (non-linearities), complex future population migration shocks etc all ***together create increasing volatility in general*** which we assess in these triptych papers.

III. Assessing NGFS and CCAR Scenarios Using ZRE:

A. Overview of ZRE:

The ZRE credit risk portfolio model was developed to support both Point-in-Time ('PIT') and Through-the-Cycle ('TTC') credit measures for Basel capital, stress testing and IFRS9.[19] We have recently adapted the solution to support CST.

ZRE utilizes two primary modules, the Scenario Forecasting Module ('SFM') (used in this first triptych paper) which applies deterministic MEV scenarios that statistically drive the industry and region credit factors using a 'bridge' model from MEV-to-Sectors. The second ZRE Module ('IRMC') is applied to run Monte Carlo simulations through the same industry and region factor segmentation. ***ZRE therefore assesses detailed historical industry and regional sector systematic credit cycle volatility***. The solution takes as inputs IRB credit models for PD, LGD and EAD and produces future predictions of ECLs by facility, borrower and portfolio segment. Consistent with current CST efforts, ZRE focuses on corporate and commercial exposures and borrowers.

For these illustrative climate results, we assess a benchmark C&I credit portfolio for the USA to project future credit losses.[20] To facilitate this, we apply the standard ZRE industry sector segmentation of 21 sectors as outlined in **Appendix I**, but we use only one regional factor for NA Corporates. In the usual ZRE implementation for a global bank portfolio in

19 See the DBS Bank Case Study for a review how a ZRE implementation supports both stress testing and IFRS9.

20 See, the FRB publication for US C&I loan loss rates.

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addition to the roughly 20 industry sectors, which are customized for each bank, we also develop custom regional factors split between corporates and FIs.

ZRE is calibrated to the full EDF history from Moody's CreditEdge from 1990-2022 which means that climate change impacts starting in the 1970s are fully embedded in the publicly traded stock prices and leverage and volatility of 37k global, corporate firms. While it is currently extremely hard to assess specific empirical climate impacts in detail, based on historical data, the EDF data foundation used to estimate systematic credit risk is just about the richest data source available to assess credit risk generally and to model detailed sectors and regions as aggregated indices of individual EDFs.

Developing Z indexes generally involves ***normalizing*** a credit-cycle indicator so that it ***has a mean value of 0 and a standard deviation of annual changes of one***. For readers unfamiliar with ZRE, **Figure 1** shows examples of four historical Z indexes – Banking, Business and Consumer Services, Machinery and Equipment and Oil and Gas. These industry sectors are derived from EDFs globally for 1990-22 and weighted by the North America region Zs to form composite Industry-Region Zs. The vertical access is normalised standard deviation with zero representing 'neutral credit conditions. When the Z index (standard deviation) is positive, PIT risks are below TTC and when the Z index is negative, in standard deviation units, PIT risks are higher than average TTC credit conditions.

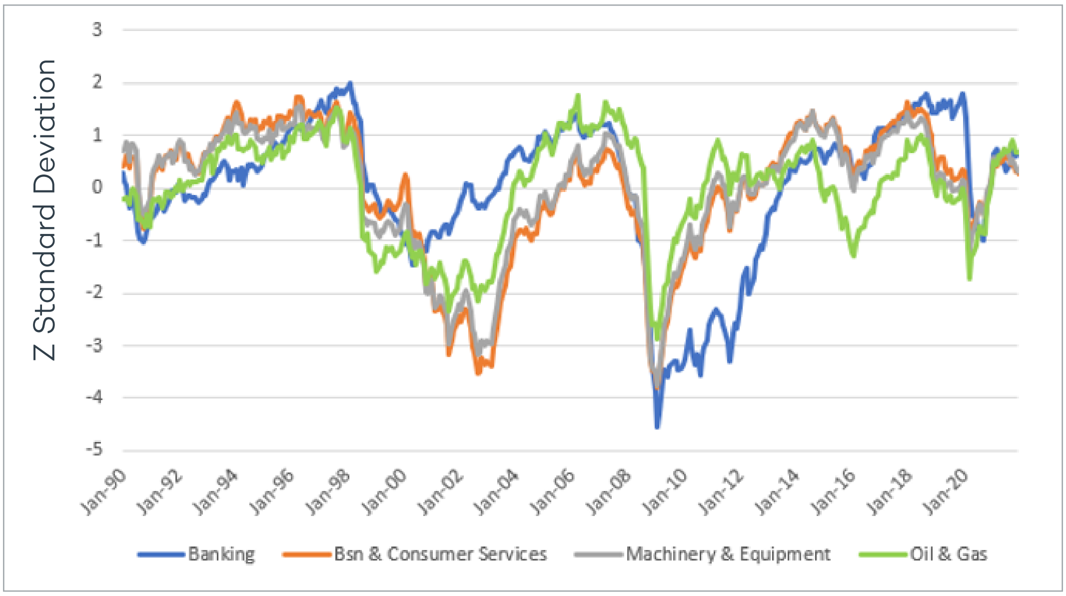

Figure 1: Four Industry Sector Z Indexes for North America
Source: Moody's CreditEdge and Z-Risk Engine

In implementing MEV-based Z indexes as presented below, we also translate GDP into a credit-cycle indicator, which requires one to first de-trend it. We accomplish that here by forming the ratio of GDP to an AR1 moving average of GDP. In this ratio, the moving average represents a debt proxy. Thus, GDP over its moving average corresponds roughly to cash flow over debt or debt service. For other credit-related series, we perform similar transformations before adding the normalizations that produce credit-cycle, Z indexes. See **Appendix I**, for more detail.

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B. NGFS Climate Scenarios Imply Uniformly Small, Credit Losses

This first climate triptych paper estimates the US, Commercial-and-Industrial (C&I), loan losses for an illustrative portfolio implied by the different NGFS climate scenarios and compares those estimates with losses both experienced in past recessions and estimated for regulatory stress scenarios. Applying the ZRE SFM we find that the NGFS scenarios imply credit losses that are small compared with those realized in past recessions. Further, the differences in losses estimated for moderate and severe, climate scenarios fall short of the differences estimated for regulatory baseline and stress scenarios. Thus, based on the climate scenarios now available, climate-change appears to have relatively little effect on credit losses.

We attribute these findings to the smoothness of the NGFS scenarios. The scenarios differ in economic growth rates but show little volatility around long-run trends. Evidently the scenarios seek to describe the long-run, welfare (consumption) losses related to climate change and not any systemic instabilities. But successful, credit models trace most defaults and losses to sharp declines in asset values and cash flows relative to trend and not to gradually slowing trends.

Large Credit Losses Occur Occasionally and Suddenly:

Experience indicates that credit crises arise in the manner described by Dornbusch's Law:[21]

> ***'The crisis takes a much longer time coming than you think, and then it happens much faster than you would have thought.'***

Paraphrased for credit, one might state this as follows:

> ***'Credit crises occur only occasionally, but, when they do, they happen suddenly, caused by sharp declines in asset values or cash flows relative to debt or debt service.'***

We see this pattern of intermittent, large events in the history of C&I loan losses (**Figure 2**). Over the past 32 years, C&I losses have risen sharply three times, in 1990-91 and especially 2001-02 and 2008-09, with each episode lasting about a year. During the 2020-21, COVID-19 induced recession, loan losses rose only moderately, perhaps due to forbearance inspired by the recognition that the downturn involved a necessary pause rather than fundamental failure of some businesses.

21 Dornbusch's Law is usually ascribed to 'overshooting' or excess volatility in foreign exchange markets but is applied here as well to credit risk. See Dornbusch, (1976).

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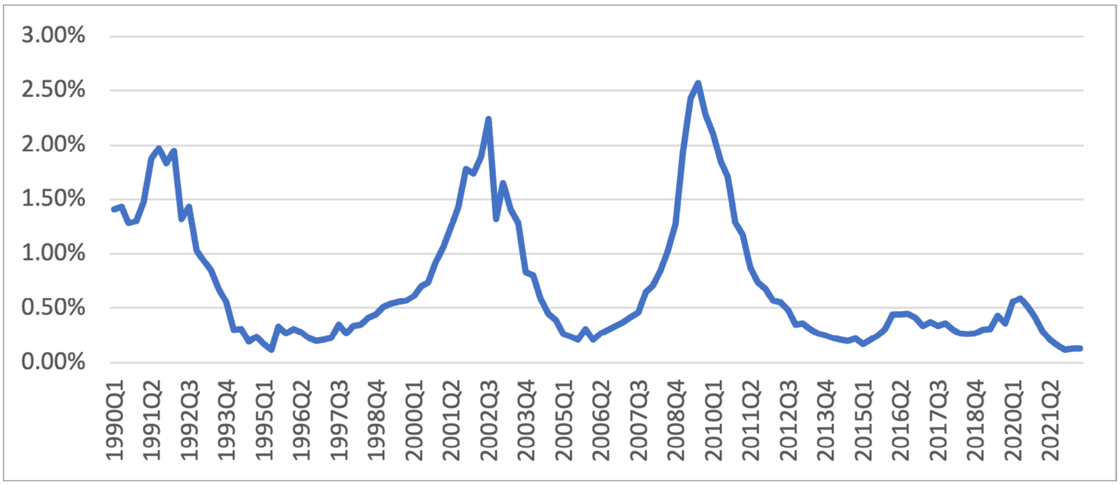

Figure 2: Annualized Charge-Off Rates (%), US C&I Loans, Quarterly, Seasonally Adjusted
Source: Board of Governors of the Federal Reserve System.

NGFS Scenarios Show Climate Change as Affecting Economic Trends and Not Volatility

The NGFS scenarios specify slightly different GDP growth rates in different climate scenarios (**Table 1**). However, the scenarios only indicate that growth rates may differ, but say nothing about cyclical instabilities around growth trends. And to obtain quarterly projections, we must resort to interpolation.[22] The result: extremely smooth GDP scenarios.

Table 1: Annual USA GDP Growth Rates in NGFS Scenarios* ** ***

NGFS Scenario	Time Period		
	2023-2030	2030-2040	2040-2050
Current Policies	5.86%	4.36%	4.03%
Below 2°C	5.85%	4.36%	4.06%
Delayed Transition	5.85%	4.35%	4.06%
Divergent Net Zero	5.86%	4.38%	4.08%
Nationally Determined Contributions (NDCs)	5.86%	4.36%	4.04%
Net Zero 2050	5.86%	4.37%	4.07%

* Real-GDP growth from 2022 GCAM.3_NGFS model. Converted to nominal-GDP growth by adding annual inflation of 2 per cent.
** Data Source: 1662723618051-V3.2%20NGFS%20Phase%203.zip.
*** We use NGFS USA GDP to be consistent with the FRB C&I Loan Loss Index we use for benchmarking.

22 We apply quarterly adjustments to be consistent with SFM inputs required for applying CCAR scenarios.

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NGFS Scenarios Imply Uniformly Smooth Credit-Factor Scenarios

Transformed into quarterly, credit-cycle, Z indexes for GDP, we get extremely smooth, credit-risk scenarios showing no major downturns and immaterial differences across scenarios (**Figure 3**). One sees very little difference between the severe climate-change, Current Policies Scenario and the moderate climate-change, Net Zero 2050 one. In contrast, the 2022 CCAR Severely Adverse Scenario has a strikingly different profile, exhibiting large deviations from the average setting of zero and from the baseline (no stress) scenario. While we don't show it here, the 2022 CCAR Baseline Scenario implies a Macro-Z path that sits almost on top of the NGFS Macro-Z paths

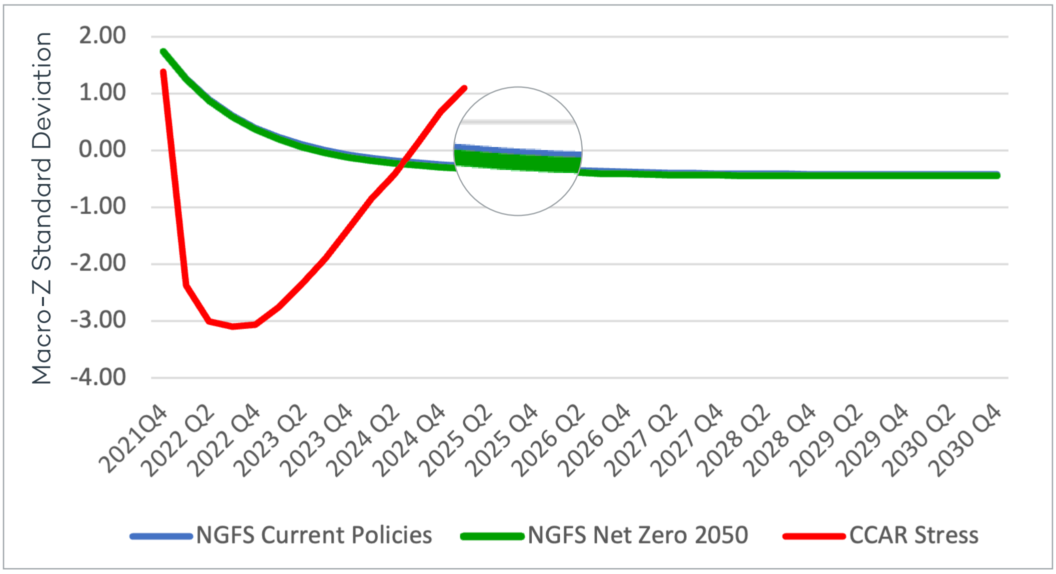

Figure 3: US Macro Credit-Factor Paths Under CCAR and NGFS Scenarios
Source: Board of Governors of the Federal Reserve System and Z-Risk Engine, NGFS.

Low Volatility NGFS Credit Scenarios Imply Uniformly Small, Credit Losses

Entering these scenarios into the SFM applied to a representative, C&I portfolio, we find that the NGFS scenarios imply uniformly small losses, with charge-off rates staying below the 1990Q1-2022Q2 average of 0.72%. In striking contrast, the 2022 CCAR Severely Adverse Scenario implies very large losses, with charge-off rates rising to more than 3x the historical average, see **Figure 4**.

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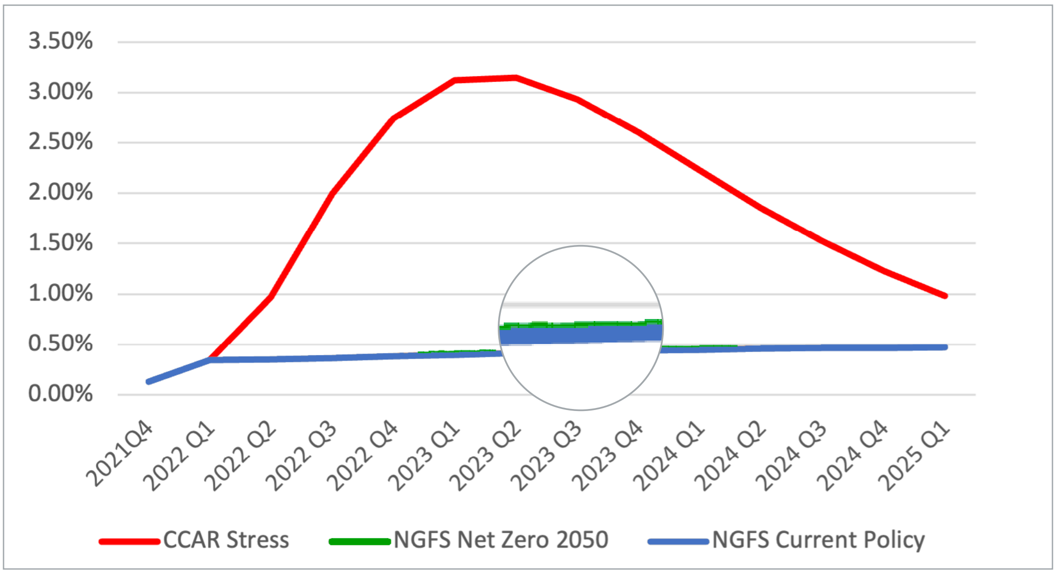

Figure 4: Estimated, C&I Charge-Off Rates: CCAR and NGFS Scenarios
Source: Board of Governors of the Federal Reserve System, NGFS and Z-Risk Engine.

As a secondary factor explaining the insensitivity of losses to the NGFS scenario, those scenarios provide only GDP projections as possible credit factors. The historical record indicates that GDP is mostly a through-the-cycle (TTC), credit indicator, not explaining much of the past variation in observed default and loss rates. When running SFM we generally find empirically that the best predictors of observed credit losses are credit spreads and equities along with GDP. As shown in **Appendix I**, page 15 for applying the SFM 'Bridge' model, the application of the CCAR scenario uses all three indicators, (spreads, equities and GDP) while applying the NGFS scenarios uses only GDP.

IV. Summary:

This first of the three climate triptych papers has reviewed industry discussion points relating to Climate Stress Test approaches currently under development at major Regulators and which generally utilize the NGFS consortium top-down scenarios. We have also provided an overview of three different empirical climate assessments we present in these triptych papers, with the first assessment presented here. The contribution of these and the three empirical assessments are presented to ***suggest an alternative, complementary credit factor approach to CST*** that seeks to assess ***systematic climate credit risk impacts more directly***.

In this first paper, we use the ZRE portfolio solution to apply NGFS scenarios for GDP into ZRE's SFM for a representative, US, C&I portfolio, and we find that the scenarios imply losses below historical averages and that differ only in very small amounts across the different scenarios. This contrasts with the substantially higher average losses predicted over the near-term in the 2022 CCAR Severely Adverse Scenario. Moreover, those, predicted stress losses stand much higher than the losses estimated in the 2022 CCAR Baseline Scenario. We attribute the insensitivity of the loss estimates currently in use in CST generally to the smoothness of the NGFS scenarios. The different, ***NGFS scenarios*** exhibit moderately different growth rates but next to no deviations from trend therefore, cet. par., they ***imply relatively limited climate induced credit risks for banks***.

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Appendix I: Scenario Forecasting Module Description:[23]

In this study, ZRE's SFM:

- draws on assumed, MEV paths,
- converts those MEV paths into paths for stationary, credit-cycle measures denoted MEV Zs,
- applies a bridge model in determining the industry and region, Z paths implied by the MEV-Z ones,
- combines the industry and region Zs into composite, industry-region Zs,
- enters the industry-region Zs into the PD, LGD, and EAD models for the facilities in the representative, C&I portfolio and thereby estimates the related, 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. 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 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.

See below for further discussion of the application of ZRE SFM in this study.

Choice of MEVs:
For the CCAR scenarios, the SFM model draws on quarterly values of the following MEVs: US GDP (cash flow proxy), Wilshire-5000, stock-price index (asset value measure), and Baa spreads (direct, credit-risk indicator). As the parenthetical comments indicate, all the selected MEVs have plausible relationships to C&I loan, credit risk. For the NGFS scenarios, the SFM model draws only on GDP.

Conversion to Macro Zs:
We convert the MEVs to macro Zs. This transformation makes the variables stationary and informative on C&I, credit risk.

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 ( ),
- 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.

23 See Forest and Aguais (2019 b) for detailed description of the SFM methodology and its application to CCAR scenarios.

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The ZS (credit spreads) series:
- starts with the US, Baa, credit-spread index,
- converts the spreads to DDs by dividing by 0.6 (which is the usual CDS conversion assumptions) and applying the negative of the inverse-normal function ( ),
- 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 ( ),
- 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.

For stock prices and GDP, the related moving averages represent debt proxies. For spreads, the moving-average adjustment removes a shift evident after recovery from the 2008-09 recession.

The different Macro-Z series generally rise together in recoveries and fall together in the 2001-02, 2008-09 and 2020 recessions, see **Figure 5**. However, prior to 2020, the Z-GDP exhibits less pronounced downturns. During the COVID-19 recession, however, the Z-GDP falls sharply, much more than the stock-price and credit-spread Zs. Clearly, this recession was idiosyncratic. Among other odd results, S&P and Moody's, rated-company default rates rose above the long-run average in 2021, but the US bank, credit-loss rates remained well-below average. Evidently, many of the defaults recorded by S&P and Moody's in 2020 were 'soft ones' in the sense that they involved payment delays but ultimately little if any loss.

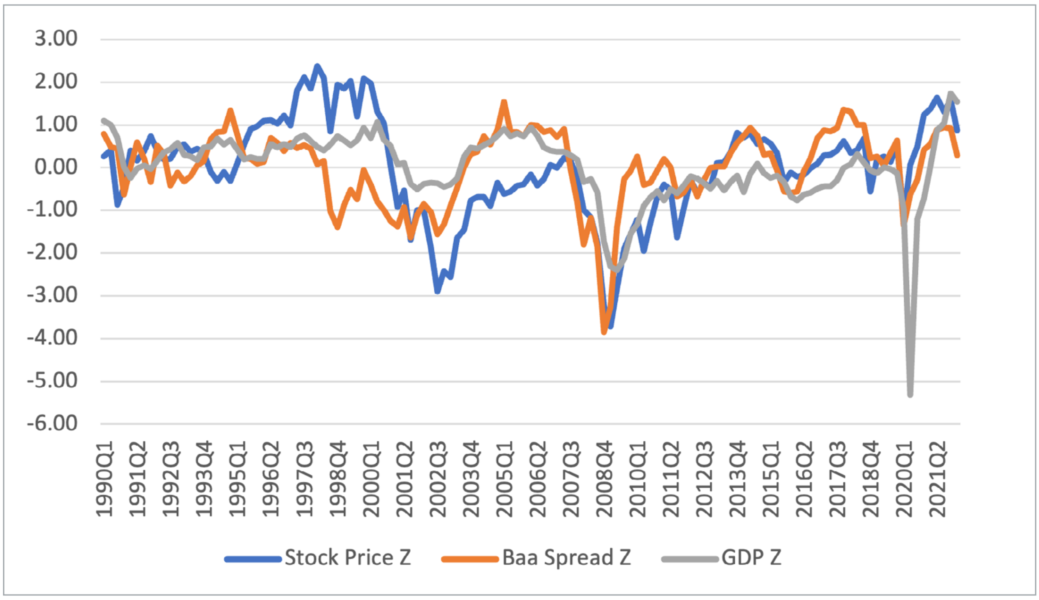

Figure 5: Macro Z Series 1990Q1 to 2022Q2
Source: Moody's CreditEdge, FRB, and Z-RiskEngine models.

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Bridge Model:
For the CCAR scenarios, the bridge model arises from a pooled, least-squares regression of one-quarter changes in the Zs for each of 21 industry and 2 regional groupings (the regional Zs applied are for NA corporates and NA FIs as we are using the benchmark FRB C&I loan loss index) on (1) one-quarter lagged values of those Zs; (2) one quarter lagged values of one-quarter changes in those Zs; and (3) current and one-quarter-lagged values of quarterly changes in the ZE, ZS, and ZG, Macro-Z indexes (**Table 2**). For the NGFS scenarios, the bridge model involves only one Macro Z, ZG. GDP is the only credit related, MEV depicted in the climate scenarios and is used generally as the primary MEV driving most climate stress test development efforts. In both cases, the estimation uses data from 1990Q3 to 2022Q1.

Table 2: Bridge Model Variables and Coefficients

Variable Type	Variable*	Parameter	CCAR Estimate	NGFS Estimate
Dependent	ΔZ			
Explanatory	Z (-1)	m_r	-0.05	-0.08
	ΔZ (-1)	m_m	0.11	0.16
	ΔZE	b(0)	0.39	0.00
	ΔZE(-1)	b(1)	0.03	0.00
	ΔZS	c(0)	0.23	0.00
	ΔZS(-1)	c(1)	0.03	0.00
	ΔZG	d(0)	0.02	0.10
	ΔZG(-1)	d(1)	0.02	0.05
Goodness of Fit	R^2		0.53	0.09

* Z denotes an industry or region, Z index. ZE, ZS, and ZG represent the Macro Zs for equity prices, spreads, and GDP, respectively. As the NGFS scenarios available do not include credit spreads and equities, for running the NGFS scenarios we only use the Macro Z GDP variable, so the table above has zero coefficients on spreads and equities as they are excluded.

Source: Z-Risk Engine analysis and assumptions

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, US C&I loans (**Table 3**). Each combination industry-region Z index arises 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 composite indexes derive from regressions of

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quarterly changes in the DDs ('Default Distance') 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 agriculture as a relevant industry.

Table 3: 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.

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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 4** below shows, the five 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 five entity risk grades using the weights shown in **Table 4** and to the 20 industry sectors using the weights shown in **Table 3**. To simplify the model, we assume that the TTC attributes are fixed over time and are the same for every industry-region segment.

Table 4: 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. 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.

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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.

Book Values, Specific Provisions, and Charge-Offs:
Book values, specific provisions, and charge-offs derive from formulas drawing on past PDs, LGDs, and EADs. Each quarterly ECL adds to specific provisions ('SP') and every, quarterly charge-off subtracts from it. We calculate the exits due to charge offs as a proportion of the beginning provision stock. We scale that proportion, so it implies that provisions remain in the stock for an average of two years. The book value has two components: the good (non-default) book ('BG') and the bad book ('BB'). By assumption, BG stays constant. We calculate BB as the totality of past, default exposures that remain as part of the provision stock. We calculate charge-off rates as charge offs divided by the starting book value.

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Appendix II: Back-Testing ZRE:

The back test validation of ZRE comes from empirical studies in which we find that:[24]

- adding ZRE's industry-region Zs to PD and LGD models drawing on financial ratios and judgemental scores increases the goodness-of-fit by a statistically significant, order of magnitude,
- applying ZRE in back tests involving a representative, C&I, loan portfolio, we get estimates that align closely with actual C&I losses (**Figure 6**), and
- replacing the long-standing random-walk models with ZRE's mean-reversion-momentum ones, we get statistically significantly better estimates of Z indices.

Table 5: Estimates of PIT-PD Models for S&P-Rated and Moody's-Rated, Non-Financial Companies

Variable	Parameter	S&P Model			Moody's Model		
		Estimate	Std Error	T-Stat	Estimate	Std Error	T-Stat
Constant	a_0	-0.39	0.06	-6.77	0.13	0.06	3.06
DD_G	a_1	1.10	0.03	3.33	0.98	0.03	-5.00
Level Shift	s_0	-0.14	0.09	-1.59	-0.11	0.09	-1.58
Slope Shift	s_1	0.24	0.05	4.73	0.29	0.05	6.16
DDGAP[1]	b	0.87	0.01	87.00	0.80	0.01	80.00

1 The DDGAP coefficient varies by region. We show above the result for global, non-financial-corporate companies. The coefficients and standard errors for the b parameters come from preliminary, instrumental-variable regressions of DDGAPs created from a sample of listed companies rated by S&P or Moody's on industry-region, DDGAPs derived from the entire sample of companies covered by CreditEdge. The resulting instruments, measuring the gaps between PIT and TTC DDs of each S&P or Moody's rating within each sector, enter the final equation with coefficient of one. Source: Authors calculations using CreditEdge data from Moody's and ratings and default data from S&P and Moody's. See Forest, L, Chawla, G, and Aguais, S, "Biased Benchmarks," Journal of Risk Model Validation, June 2015. Also, at https://www.z-riskengine.com/media/1026/biased_benchmarks-after-jrmv-comments-draft-main-and-appendix.pdf

24 See Forest and Aguais, (2019 a) for the full back test validation analysis of ZRE generally and (2019 b) for the details of applying and validating the ZRE SFM.

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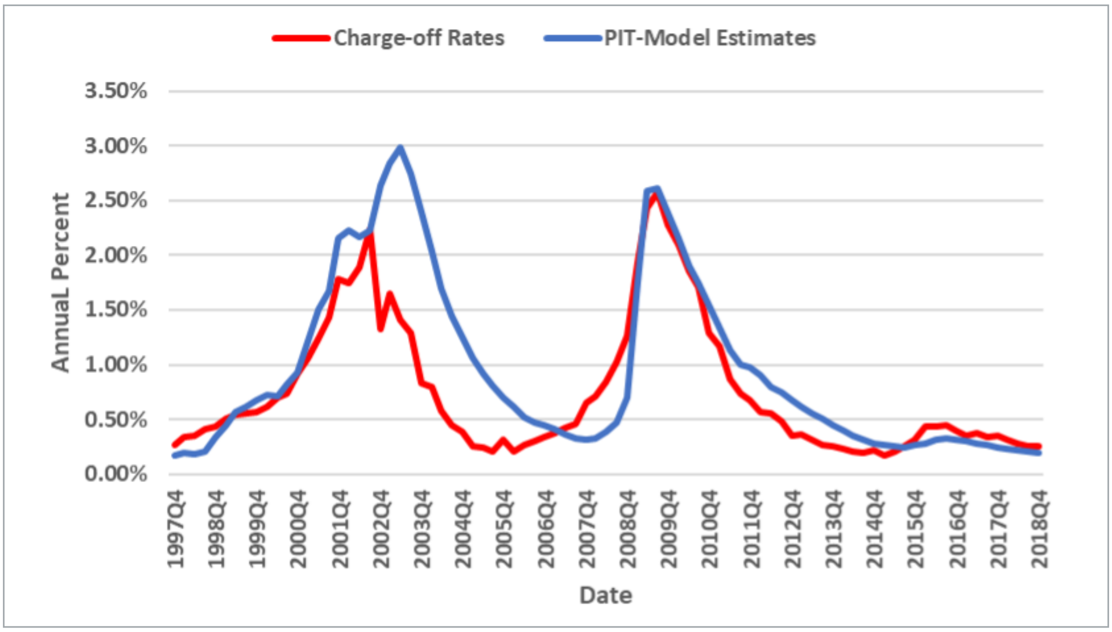

Figure 6: Back Test Over 1997Q4-2018Q4 for a C&I-Loan Portfolio
Source: Board of Governors of the Federal Reserve System, Z-Risk Engine.

See Forest, Aguais (2019 a)

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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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