



Developing an Empirically-Based Climate Credit Risk Stress Test Framework

Summary of Findings from Our 'Climate Credit Risk
Triptych' Papers*

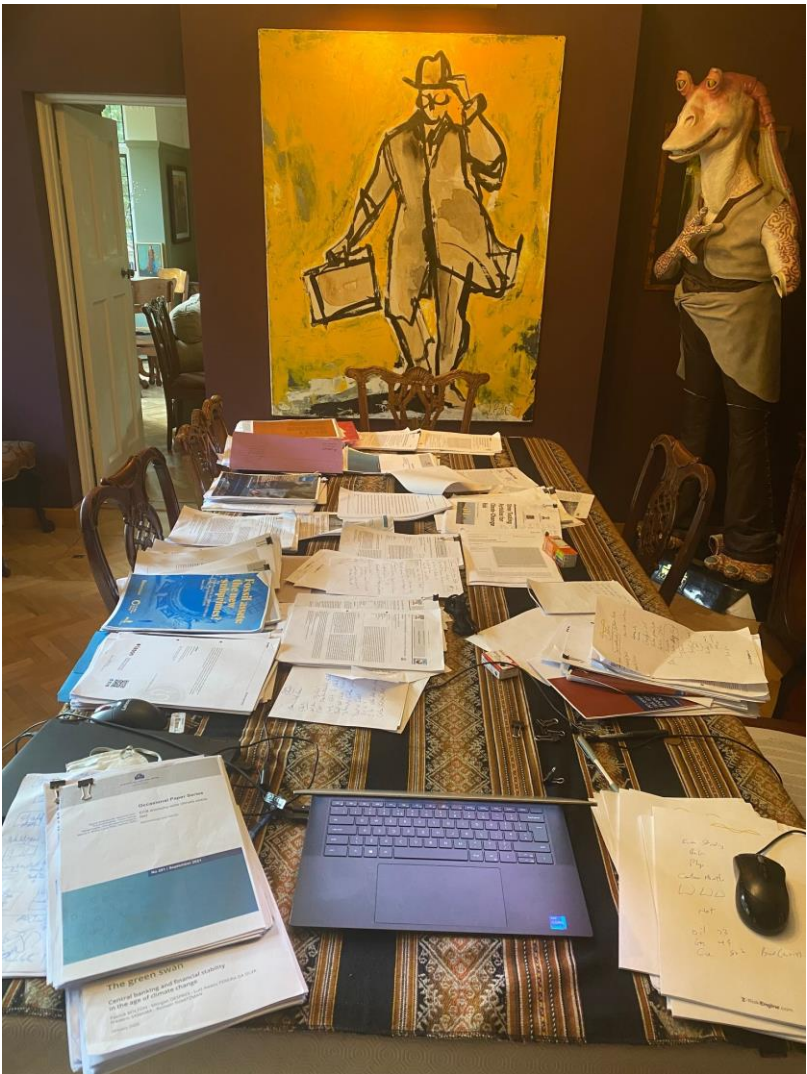
RiskMinds International, Barcelona, November 9, 2022

Scott D. Aguais, Ph.D.
Managing Director, Z-Risk Engine
saguais@z-riskengine.com

**Forthcoming in: 'Decision Making for the Net Zero
Transformation: A Compendium of Best Practice', Frontiers Journal*



Scott's 'Climate Research' Dining Room – Jar Jar Binks as a Climate Research Observer – My 'Personal Penance for Printing Climate Papers'



Key Points – Long Time Horizons, Degree of Uncertainty & Limited/No Data - Climate Stress Test Modelling for Banks is **HARD**

- Climate stress tests, led by NGFS & Regulators to-date - extremely early in the lifecycle
- Focus: **physical risk & ‘carbon transition’** (emissions & carbon mitigation) mostly at the **individual company-level**
- Risk models generally require:, (1) reasonable candidate set of **‘future states of the world’** & (2) **related ‘estimated probabilities’**
- Current climate stress test approaches **may not satisfy** either objective of risk models
- Climate driven credit risks in the aggregate will be driven by a **broad range of potential shocks – not trends** in aggregate economic measures
- Focus of the presentation:
 - High-Level ‘Framework’ for Climate Stress Testing
 - Briefly review ECB climate stress test approach & ‘complementary’ multi credit factor approach (ZRE)
 - Highlight role of broad increases in climate-driven volatility
 - Summarize *Climate Change Credit Risk Triptych* papers three empirical climate risk assessments
 - Implementation ideas for extending framework

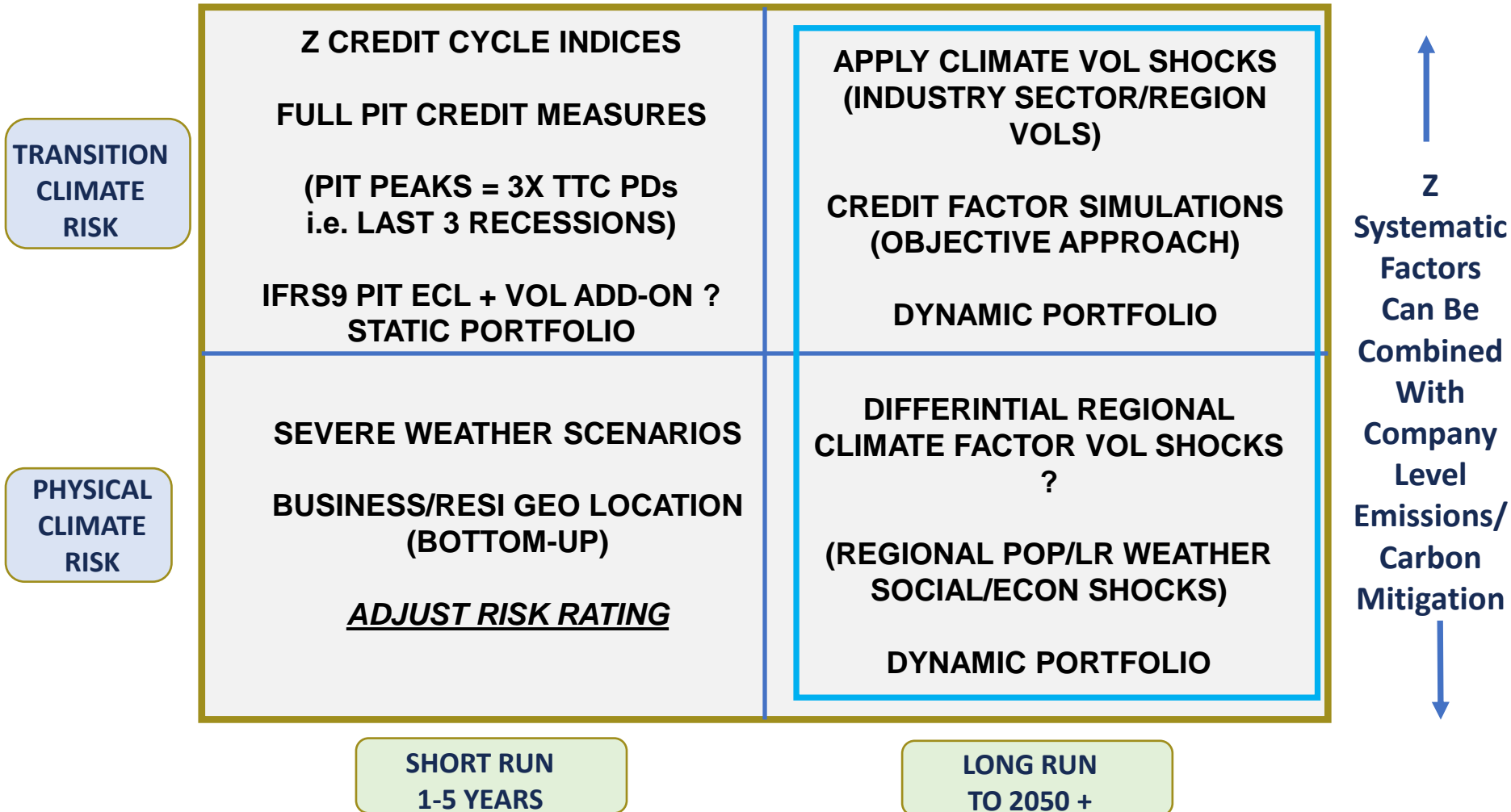
Z-Risk Engine – Multi Credit Factor Solution – Corp & Commercial

- Implements key PIT/TTC framework developed over last 18 years (see biblio)
- Calibrated to market-based public-firm default models (EDFs)* - full PIT PD, LGD & EAD
- Applies **Systematic Credit Cycle Indices** (CCIs) for custom industry sectors & regions
- Runs **deterministic** stress MEV scenarios (CCAR, ECB) or **simulations** of MEV, industry/region factors
- Supports IFRS9/CECL & Stress Testing
- See, **DBS Bank (Singapore) Case Study** for ZRE implementation & business benefits
- **Triptych papers** published at RiskMinds highlight empirical application to climate stress testing which is complementary to current approaches

** We use Moody's CreditEdge EDFs for the Climate Change Credit Risk Triptych empirical assessments presented here*

Simplified Climate Stress Test Framework – Credit Risk

Triptych Papers Apply NGFS GMT-to-Vol Illustrative Vol Increases



Overview - Climate Change Credit Risk Triptych Papers:

Climate Risk Triptych Papers: Three Empirical Assessments of Future Potential Climate Impacts on Wholesale Credit Losses:

- *Paper One: 'Smooth' NGFS Climate Scenarios Imply Minimal Credit Losses:*
 - Highlight key Climate Stress Test ('CST') current industry discussion points
 - Empirically compare NGFS US GDP scenarios with CCAR Severely Adverse stress test – **MEV BRIDGE MODEL**
 - ZRE (Est, Moody's CreditEdge EDFs 1990-22) to project credit loss rates to 2050 for NGFS & CCAR severely adverse scenario
- *Paper Two: Climate Change Volatility Effects Imply Higher Credit Losses:*
 - Apply NGFS Global Mean Temperature ('GMT') scenarios using an illustrative GMT-to-Volatility 'model' to simulate (1000 sims) climate impacts on **industry/region systematic factors**
 - Assess credit losses for an illustrative US benchmark C&I portfolio - expected, 95% and 99% 'tail' credit losses
- *Paper Three: Climate Change Macro Volatility Effects Imply Higher Credit Losses:*
 - Apply NGFS Global Mean Temperature ('GMT') scenarios using an illustrative GMT-to-Volatility 'model' to simulate (1000 sims) climate impacts on **US macro-economic factors and indirect industries/regions**
 - Assess credit losses for an illustrative US benchmark C&I portfolio, - expected, 95% and 99% 'tail' credit losses
 - Compare expected, 95% and 99% 'tail' credit loss results from papers One and Two

Key Industry Climate Risk Stress Test Discussion Points

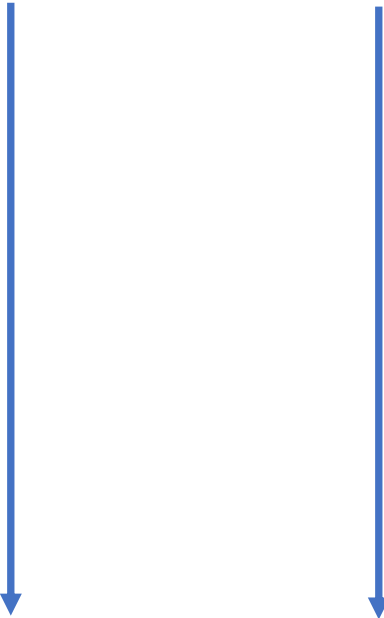
Climate Risk Triptych Papers Consider: Key Climate Stress Test Discussion Points:

1. Use of **deterministic scenarios** in the NGFS approach that have only **limited empirical foundations**
2. Application of IAM-Style, '**trend-like**' scenarios which don't consider **unexpected economic shocks** which are the usual driver of **systematic credit risks**
3. Lack of incorporation of more **extreme, 'near-catastrophic'** future climate 'states of the world' (BUT 'DICAPRIO SCENARIO' UNTRACTABLE)
4. 'Top-down' ('IAM') approaches support only a limited ability to assess **granular, detailed Industry/region credit risk drivers**
5. Developing more detailed **climate narratives** could support **improved economic logic** in assessing climate credit stresses

ECB Climate Stress Test vs ZRE – Detailed Industry/Region Credit Factor Models Assess Systematic Risks Not Possible With ‘Top-Down’ MEVs

ECB CLIMATE STRESS TEST APPROACH

NGFS COUNTRY GDP SCENARIOS



Add Carbon Taxes & Physical Risk Damage That Impact Company-Level Leverage & Profitability

$$PD = F(\text{Leverage, Profitability, Age, GDP})$$

MULTI-COUNTRY MEV SCENARIOS: GDP, CREDIT SPREADS, EQUITIES

CONVERTED TO ‘MACRO Zs’

BRIDGE MODEL

INDUSTRIES

- AEROSPACE & DEFENSE
- AGRICULTURE
- BANKING
- BASIC INDUSTRIES
- BUSINESS & CONSUMER SERVICES
- CHEMICALS & PLASTIC PRODUCTS
- CONSTRUCTION
- CONSUMER PRODUCTS
- FINANCE, INSURANCE & REAL ESTATE
- MOTELS & LEISURE
- MACHINERY & EQUIPMENT
- MEDIA
- MEDICAL
- METALS
- MINING
- MOTOR VEHICLES & PARTS
- OIL & GAS
- RETAIL & WHOLESALE TRADE
- TECHNOLOGY
- TRNSPORTATION
- UTILITIES

CORPS/FIS

- NORH AMERICA
- LATAM
- EUROPE
- UK
- GERMANY
- FRANCE
- NORDICS
- CHINA
- SE ASIA
- AUSTRALIA
- MIDDLE EAST
- UTILITIES

CLIMATE SEGMENTATION CUSTOMISED FOR INDIVIDUAL BANKS

PD/LGD/EAD

ECB Model for Climate-Related Credit Losses - Summary

Climate change in the ECB model affects financial ratios & thereby PDs

- *PDs sensitive to book leverage, profitability, age of company, & regional GDP:*
 - *Leverage = Debt/Assets*
 - *Profitability = Earnings/Assets*
- *Climate change causes PDs to rise as a consequence of:*
 - **Upward trending leverage** – *debt increases with assets prior to damage whereas assets net of rising damage write-offs enters into the leverage ratio*
 - **Downward trending profitability** – *costs rise as assets prior to damage, carbon taxes, and property-and-casualty insurance premiums increase, but revenues tied to assets net of damage rise less than proportionately*
- *ECB model ignores systematic factors (cycles) & so is under estimating credit losses and may be understating climate effects*

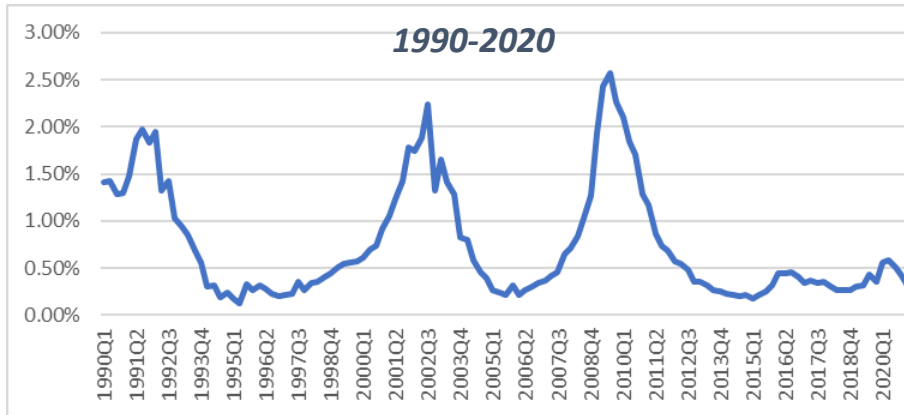
Add Systematic Z indices to the ECB PD model

- PD models:
 - Existing Close-to-TTC: $PD = F(\text{Leverage, Profitability, Age, GDP})$
 - Improved PIT: $PD = G(\text{Leverage, Profitability, Age, GDP, Z})$
 - Existing model linear whereas improved model would be Probit or Logit
- Z indices will make PDs PIT, **sensitive to credit cycle**:
 - Z sims will produce PD sims exhibiting cycles
 - TTC PDs will increase due to convexity of Probit or Logit model within the relevant range
- If climate change **causes Z vols to rise**, this will produce larger climate effects – Bigger ‘Tail’ Credit Losses in Recessions cet par

1990-22 Credit Losses Exhibit Substantial Systematic Credit Cycles - NGFS Scenarios Vary However, Only in Small Changes to Trend GDP Growth Rates

See Triptych Paper One for the Details

Annualized US C&I Charge-Off Loss Rates (%)



Source: Board of Governors of the Federal Reserve System

Annual US GDP Growth Rates in NGFS Scenarios

Table 2: 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.

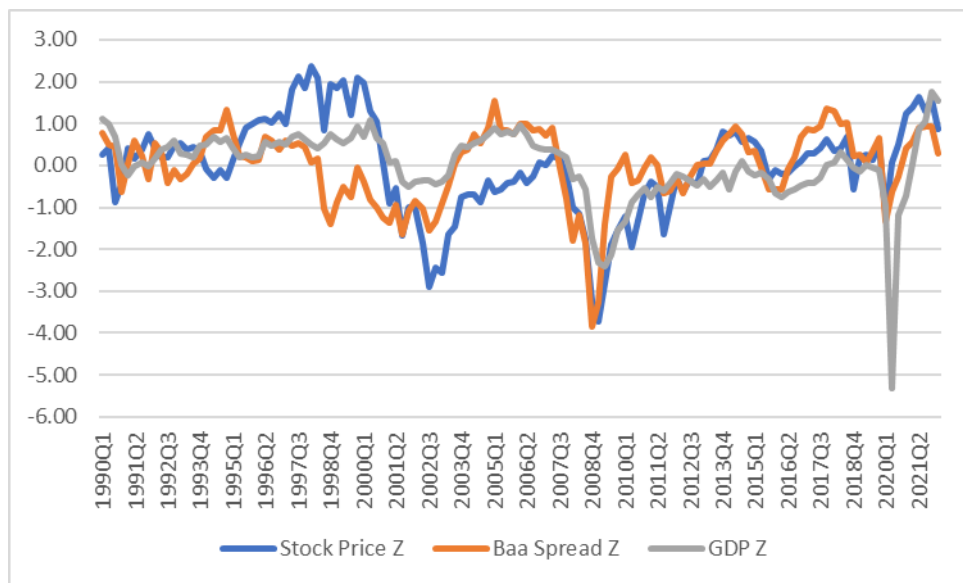
*** We use NGFS USA GDP to be consistent with the FRB C&I Loan Loss Index we use for benchmarking.

Source: NGFS

Appendix: Historical Macro Factor ‘Z’ Paths and Macro-Factor ‘Bridge’ Model Variables and Coefficients

- ‘Bridge’ model arises from pooled least-squares regressions of Industry/Region Zs and MEVs
- **NGFS scenarios** – ‘bridge’ model uses **GDP only**
- **CCAR scenarios** – ‘bridge’ models use equities (ZE), credit spreads (ZS) and GDP (ZG)
- 20 industry segments (Z) and NA corps/FIs to support benchmarking to US C&I Loan Loss Index
- **Estimated 1990:Q3 to 2022:Q2**

1990-21 HISTORICAL Z MACRO FACTORS



Source: Moody’s CreditEdge, FRB, and Z-Risk Engine

CCAR/NGFS MACRO-FACTOR ‘BRIDGE’ MODEL

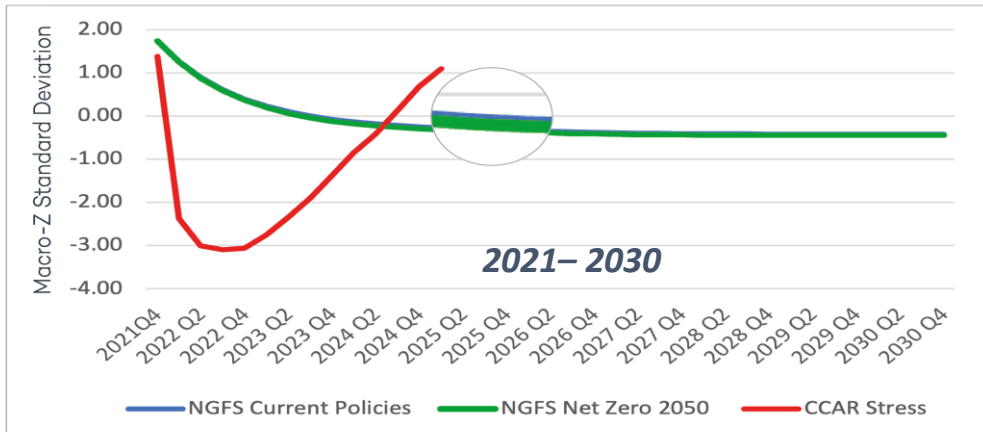
Variable Type	Variable*	Parameter	CCAR Estimate	NGFS Estimate
Dependent	ΔZ			
Explanatory	Z (-1)	m_r	-0.05	-0.08
	ΔZ (-1)	m_m	0.11	0.16
	ΔZE	$b(0)$	0.39	0.00
	$\Delta ZE(-1)$	$b(1)$	0.03	0.00
	ΔZS	$c(0)$	0.23	0.00
	$\Delta ZS(-1)$	$c(1)$	0.03	0.00
	ΔZG	$d(0)$	0.02	0.10
	$\Delta ZG(-1)$	$d(1)$	0.02	0.05
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: Moody’s CreditEdge, FRB,, NGFS and Z-Risk Engine

Estimated CCAR Stress Scenario Driven by Unexpected Economic Shocks – NGFS Scenarios Exhibit Minimal Systematic Future Credit Risks

ZRE US Macro Credit Factor Paths: CCAR & NGFS Scenarios



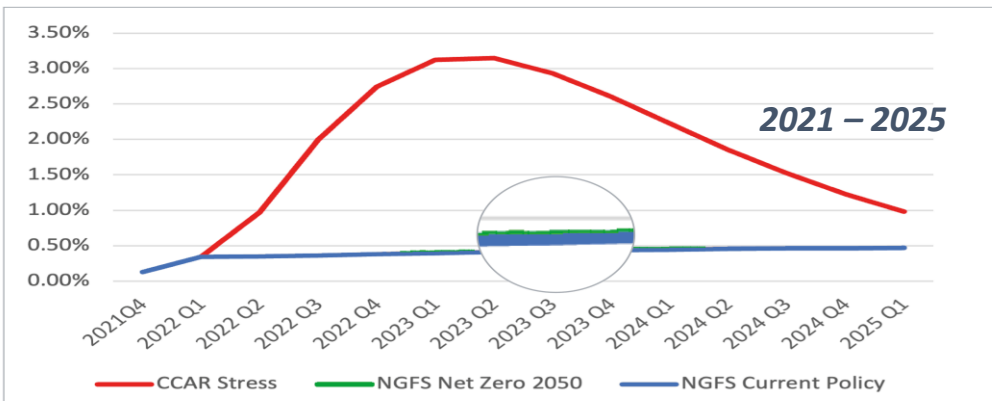
Source: Moody's CreditEdge, FRB, NGFS and Z-Risk Engine

See *Triptych Paper One* for Details

Estimated Credit Factor Paths:

- CCAR Severely Adverse Scenario and Two NGFS Scenarios
- Figure plots future macro-factor paths in standardized 'Z' terms (zero mean, unit variance) with **standard deviation** on the vertical axis
- **CCAR scenario red line shows a negative 'shock' of roughly 3 standard deviations**

Est C&I Credit Loss Rates: CCAR & NGFS Scenarios



Source: Moody's CreditEdge, FRB, NGFS and Z-Risk Engine

Estimated Credit Losses:

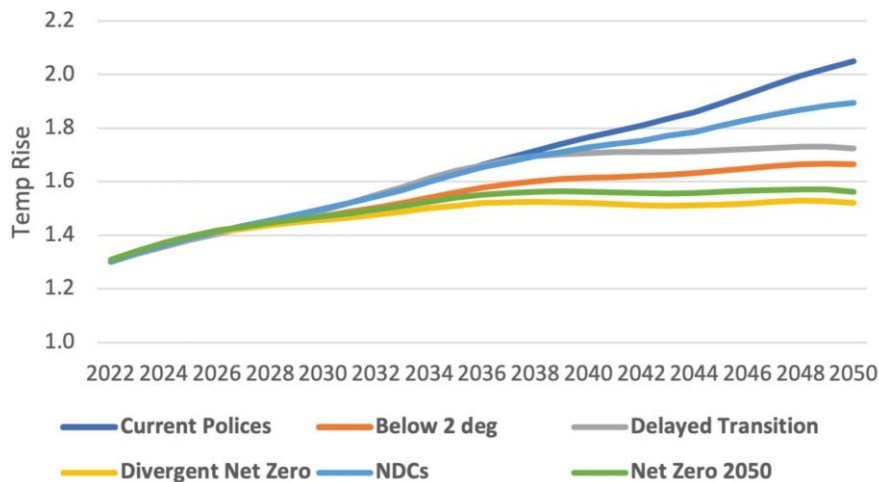
- NGFS scenarios show minimal increases in systematic credit loss rates
- CCAR scenario, red line shows substantial increase in projected credit loss rates
- See *Triptych Paper One* for details on the models utilized

To Assess Future Climate Systematic Credit Impacts We Utilize NGFS Scenario GMT Paths to Derive an Illustrative GMT-to-Volatility Multiplier

See *Triptych Paper Two* for the Detailed Analysis:

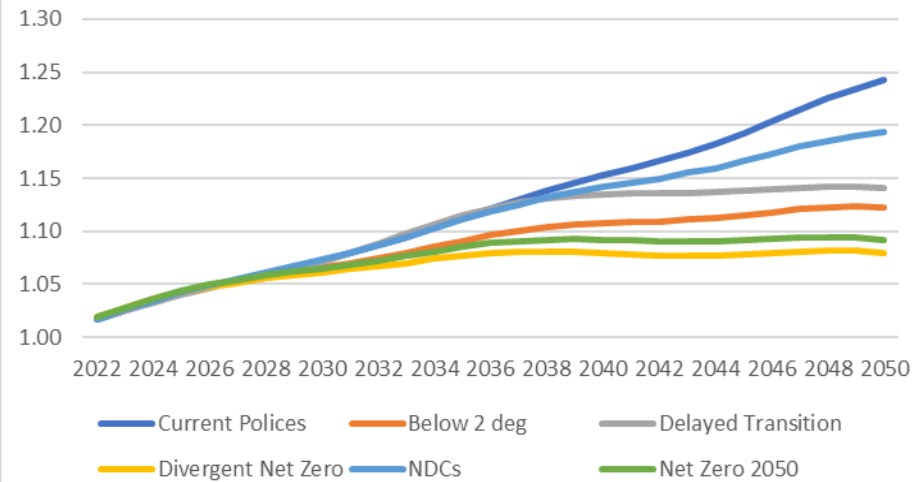
- Credit Volatility Multipliers derived from simplified, illustrative GMT-to-Vol 'model' for each NGFS scenario
- The Credit Multipliers increasingly boost future volatility of the credit factors in the credit loss simulations

TO 2050 GMT TEMPERATURE INCREASES IN NGFS SCENARIOS



Source: NGFS

TO 2050 GMT-IMPLIED CREDIT VOLATILITY MULTIPLIERS FOR NGFS SCENARIOS



Source: NGFS and Z-Risk Engine

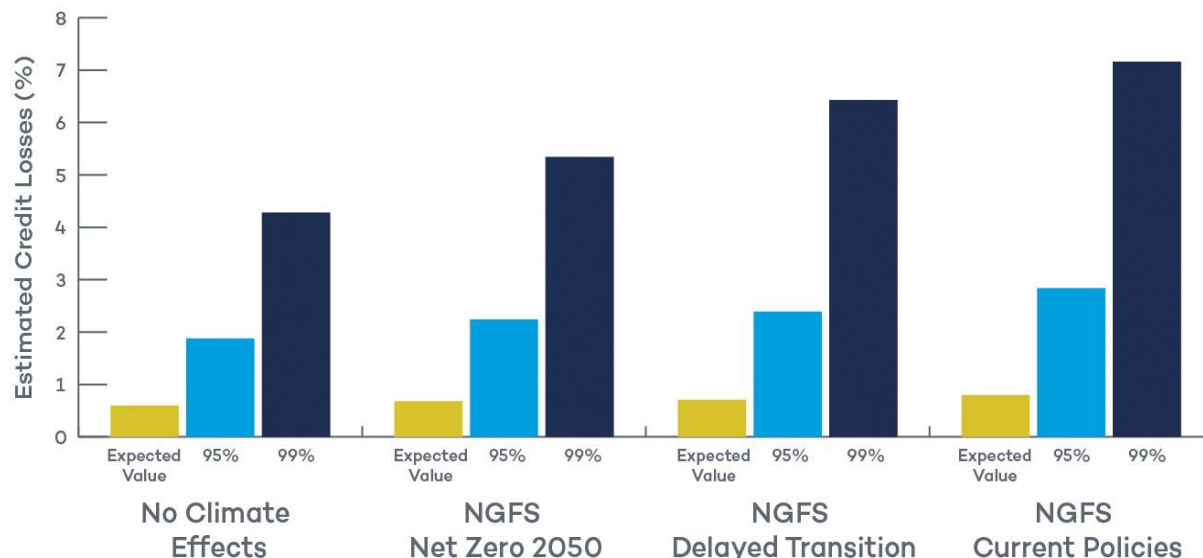
2050 Credit Losses from GMT Climate Multipliers: ZRE INDUSTRY/REGION

Credit Factor Simulation Results – Expected & Tail Results – See Paper Two

Estimated 2050 Credit Losses:

- GMT-to-Vol assumption
- 20 Industry/NA Regions simulations (1000)
- NGFS Compared to 'No Climate Effects' (no vol increase)
- Representative C&I portfolio, industry weights & risk grade assumptions in Appendix

Est 2050 Credit Losses for US C&I Portfolio: NGFS Scenarios vs 'No Climate' Effects



Source: Moody's CreditEdge, NGFS and Z-Risk Engine

Est 2050 Credit Losses for US C&I Portfolio: NGFS Scenarios vs 'No Climate' Effects

Statistic	Credit Losses 2050						
	No Climate Effects Baseline	Relative to Limit			Relative to 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: Moody's CreditEdge, NGFS and Z-Risk Engine

FOR COMPARISON 'GREAT RECESSION' OBSERVED C&I CREDIT LOSSES WERE ABOUT 2.3% COMPARED TO A LONG-RUN AVERAGE OF 0.72%

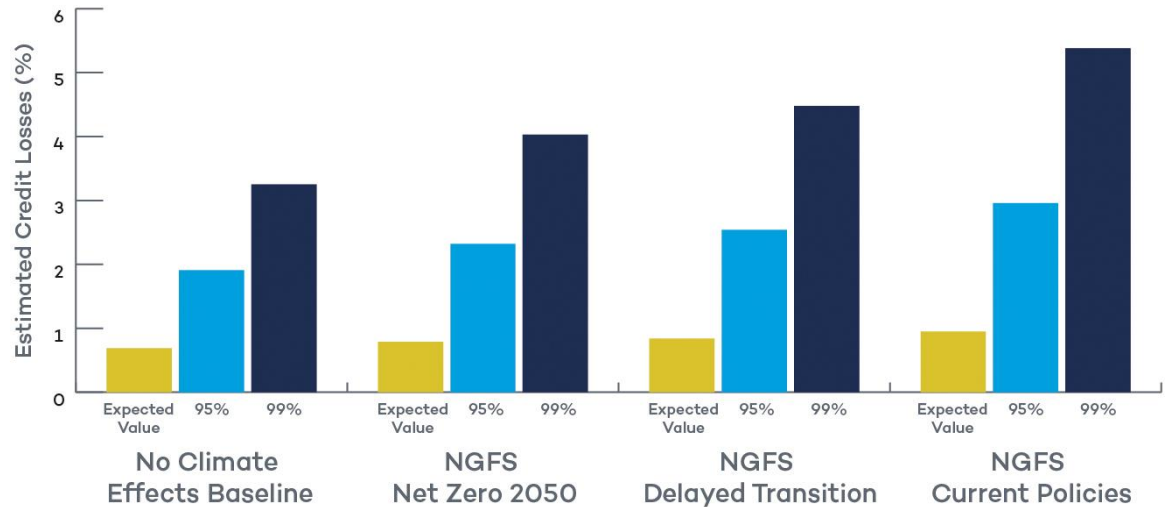
2050 Credit Losses from GMT Climate Multipliers: ZRE **MACRO** Credit Factor Simulation Results – Expected & Tail Results – See Paper Three

Estimated 2050 Credit Losses:

- GMT-to-Vol assumption
- Macro Factor Simulations (1000): Credit Spreads, Equities and GDP
- Macro-Factor ‘Bridge’ Model includes Industry/Region effects indirectly
- NGFS GMT Compared to ‘No Climate Effects’ (no vol increase)
- Representative C&I portfolio, industry weights & risk grade assumptions in Appendix

FOR COMPARISON ‘GREAT RECESSION’ OBSERVED C&I CREDIT LOSSES WERE ABOUT 2.3% COMPARED TO A LONG-RUN AVERAGE OF 0.72%

Est 2050 Credit Losses for US C&I Portfolio: NGFS Scenarios vs ‘No Climate’



Source: Moody’s CreditEdge, FRB, NGFS and Z-Risk Engine

Est 2050 Credit Losses for US C&I Portfolio: NGFS Scenarios vs ‘No Climate’

Statistic	Credit Losses 2050						
	Relative to Limit				Relative to Baseline		
	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

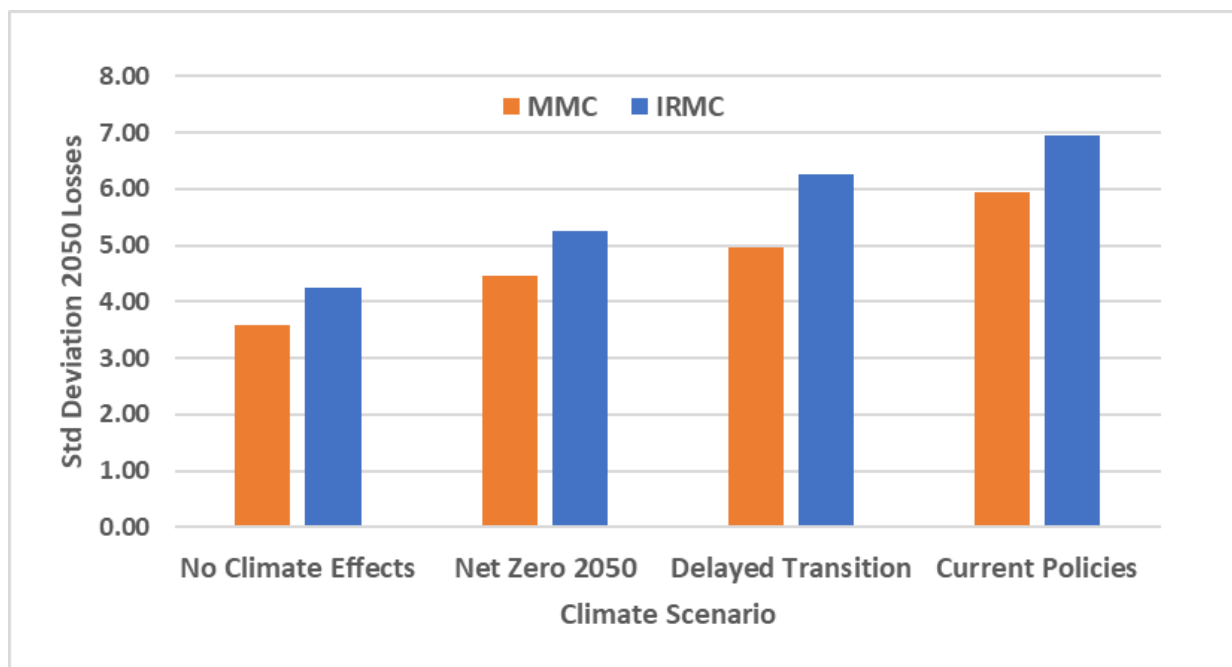
Source: Moody’s CreditEdge, FRB, NGFS and Z-Risk Engine

Comparing 2050 Projected Climate Credit Losses – Industry/Region Simulations vs Macro-Factor Simulation Results

See Triptych Paper Two and Three for the Details:

- ‘IRMC’ is the ZRE ‘Industry Region Monte Carlo’ approach (paper Two)
- ‘MMC’ is the ZRE ‘Macro Monte Carlo’ approach (Paper Three)

C&I Loss Volatilities Under Alternative Climate Scenarios Under Two ZRE Approaches



Source: Moody's CreditEdge, FRB, NGFS, and Z-Risk Engine

Risk and Industry Mix Attributes of the Illustrative C&I Benchmark Portfolio Used in the Three Empirical Assessments of Climate Risk

Benchmark C&I Portfolio Applied in all Three Triptych Papers

TTC Risk Attribute Assumptions for C&I Benchmark Portfolio

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 Analysis and Assumptions

Industry Sector Composition – Benchmark Portfolio

Weight	C&I Industry	Associated Region Grouping
1%	Aerospace and Defense	North America Corps
5%	Banking	North America FIs
5%	Basic Industries	North America Corps
20%	Business and Consumer Services	North America Corps
	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
	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 Analysis and Assumptions

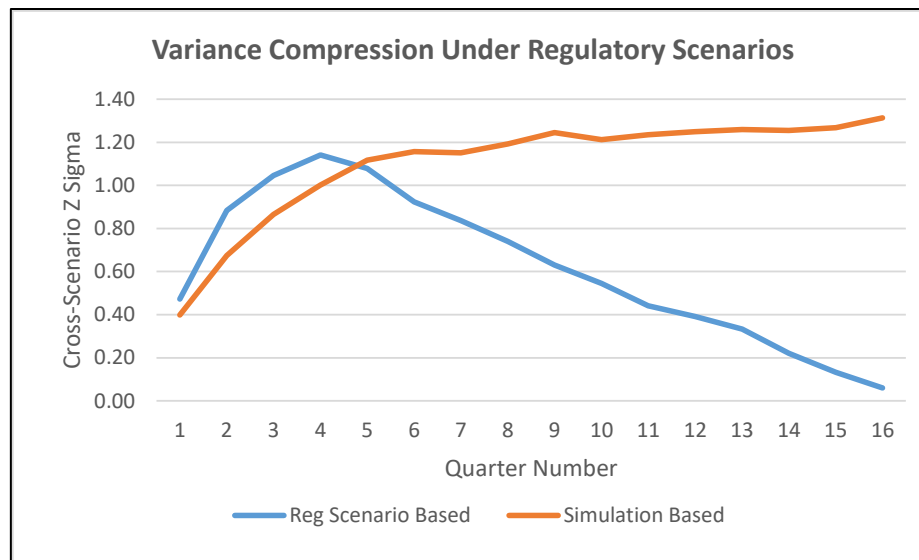
Key Questions Impacting Implementation of Integrated Credit Factor Approach With Carbon Mitigation & Extreme Volatility (Social, Weather, Political etc)

- Scenario Generation: Simulated vs Deterministic:
- **‘Variance Compression Bias’** – Larger Number of Deterministic Scenarios Required (if not running simulations)*
- Extreme ‘Existential’ (DiCaprio) Scenarios Need to be Excluded (Stern/Stiglitz)
- Linking Scenario Detailed Climate Narratives to Scenario/Model Assumptions (See Real World Stress Test Group)
- Capability to run standardized (NGFS) scenarios & customized bank scenarios
- **Revisit Industry Sector Segmentation** to Expand ‘Brown vs Green’ – Requires Full Bottom-Up CreditEdge EDFs Segmentation for 37k Companies
- Expand Regional Z Segmentation to highlight differential weather impacts
- **Estimate Empirical NGFS/Other Scenario GMT-to-Vol Model – Try Using Cat Bonds ?**

** See Forest & Aguais, 2019 c in biblio*

Running Limited Deterministic Scenarios for Climate Risk Like Reg Cap Scenarios - Leads to Reduced Future Variability Compared to Simulated Scenarios

- Need large numbers of probabilistic scenarios to describe future risk distributions of credit conditions including the possibility of recession at any time
- Applying a few climate scenarios, similar to regulatory or ICAAP scenarios designed to test the adequacy of current capital resources, **front load variations and converge on a baseline** after two to three years; this counterfactual, **variance compression** produces downward biases in ECLs at longer tenors – **‘Variance Compression Bias’**



See, ZRE Case Study, 2019, 'Variance Compression Bias in Expected Credit Loss Estimates Derived from Stress-Test Macroeconomic Scenarios', ZRE web site.

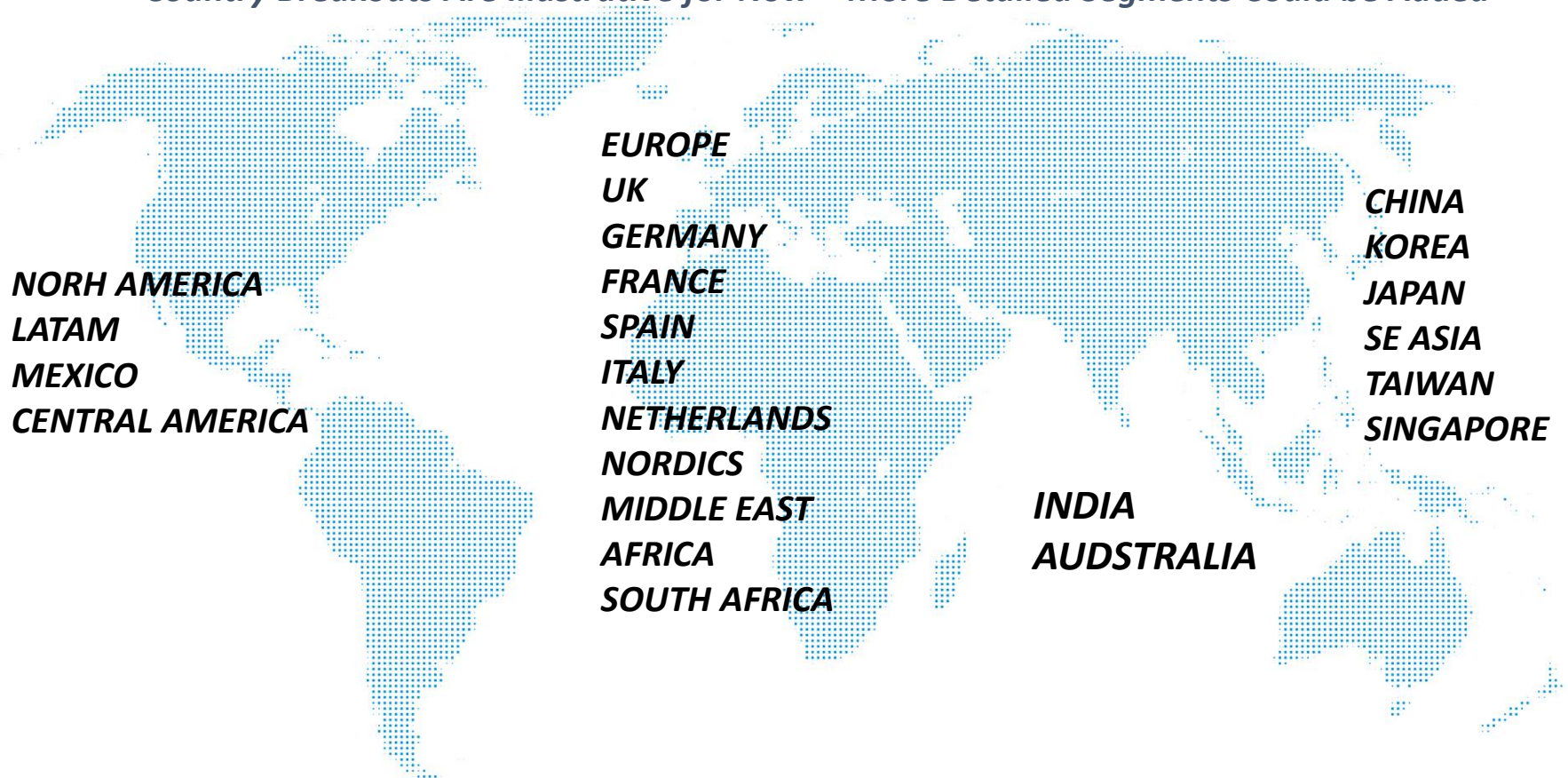
Applying Detailed Regional Z Factor Segmentation Derived from EDFs to Assess Systematic Regional Potential Climate Impacts

Custom Z CCI Creation Dependent Upon Total Public Corps Split Corps/Fis

Extreme Weather Indices Show Current Volatility Has a Regional Dimension

Region Factor May Impact Systematic Population Migration/Social Shocks etc

Country Breakouts Are Illustrative for Now – More Detailed Segments Could be Added



Illustrative Triptych Assessments vs Bank Implementation

MEVs

INDUSTRY
SEGMENTATION

REGION
SEGMENTATION

CREDIT PD/LGD

CREDIT
EXPOSURES

TRIPTYCH PAPERS ILLUSTRATIVE LOSS IMPACTS

- NGFS - GDP ONLY
- STANDARD 20 SECTORS
- NORTH AMERICA
- ILLUSTRATIVE RISK GRADES & MODELS
- ASSUMED \$600 MILLION

APPLICATION TO A BANK WHOLESALE PORTFOLIO

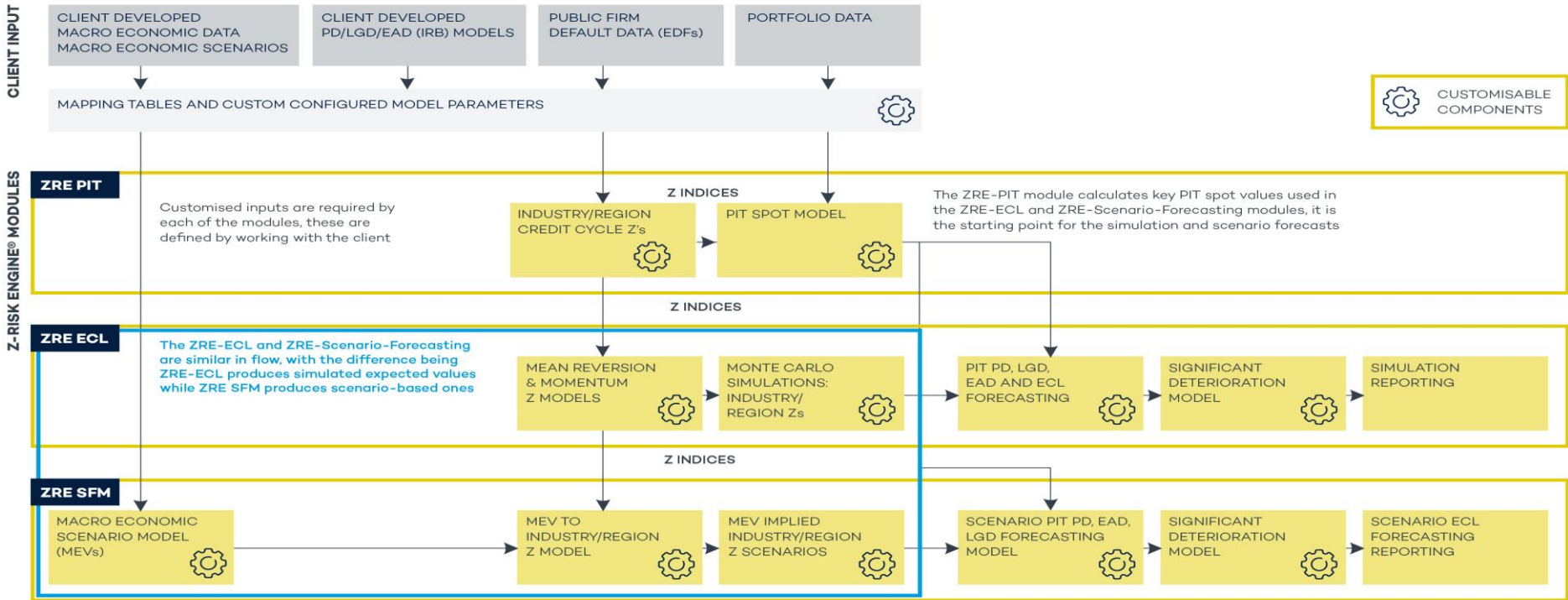
- GDP, SPREADS, EQUITIES
- CUSTOM CLIMATE SEGMENTATION (EDF BOTTOM UP)
- CUSTOM REGIONS/COUNTRIES
- BANK IRB CREDIT MODELS
- INTERNAL BANK EXPOSURES

Applying Expanded ZRE ‘Levers’ To Refine Triptych Papers Preliminary Approach

- Apply **Differential Industry Sector/Region** Factor Volatility Increases (Decreases ?)
- Develop **Time-Dependent Scenario Paths** – ‘Brown vs Green’ Increasing & Decreasing Aggregate TTC PDs
- **Expand Regional Segmentations** to Add Individual Countries Where Possible Including Larger Number of Country ‘Bridge’ Models
- **Integrate Industry/Region Factor Approach With ‘Bottom-Up’ Emission Intensities & Carbon Mitigation**
- Linking Scenario Detailed Climate Narratives to Scenario/Model Assumptions (See Real World Stress Test Group)
- **Dynamic Portfolio** - Changing Future Characteristics Supports Long Run Climate Strategy Assessment:
 - Change Industry/Region Sector Weights
 - Change Risk Grade Distributions
 - Change Lending Product Mix

Current ZRE Solution in Python for IFRS9/Stress Testing Can Support Climate Stress Testing - Using Multi-Factor Systematic Risk Framework

- Multi-factor approach already projects IFRS9 ECLs using either of two approaches:
 - Deterministic MEV Scenarios: Assess ECLs using MEV scenarios with systematic Z factors
 - Or, simulation-based Z credit factor approach: industry/region second-order Z credit cycle factors
- Climate Triptych Papers apply ZRE to climate risk



Aguais et al PIT/TTC Ratings, ZRE and Climate Risk Publications

Aguais, S, and L. Forest, (2022), 'Climate Change Credit Risk Triptych, Paper One: Smooth NGFS Climate Scenarios Imply Minimal Impacts on Corporate Credit Losses', ZRE Working Paper Published at RiskMinds International, November 7.

Aguais, S, and L. Forest, (2022), 'Climate Change Credit Risk Triptych, Paper Two: Climate Change Volatility Effects Imply Higher Credit Losses', ZRE Working Paper Published at RiskMinds International, November 7.

Aguais, S, and L. Forest, (2022), 'Climate Change Credit Risk Triptych, Paper Three: Climate Change Macro Volatility Effects Imply Higher Credit Losses', ZRE Working Paper Published at RiskMinds International, November 7.

Aguais, Scott, (2022), 'Musings on Long Run Climate Stress Test Modelling for Banks', presentation, Marcus Evans, Climate Stress Testing, June 16, 2022, London, ZRE website.

Z-Risk Engine Case Study, (2022) 'Supporting Integrated IFRS 9 and Stress Testing at DBS Bank', August, https://www.z-riskengine.com/media/myukq4mu/zre_dbs_case_study_aug22.pdf

'Automating a Centralised IFRS9 Architecture to Reduce BAU Operating Expense Budgets by 40%', ZRE Insights, ZRE Web Site, February 2022, forthcoming.

'IFRS9 Credit Model budgets can be reduced by up to 30% - by using more efficient model architecture', ZRE Insights, ZRE Web Site, November 2021.

Forest, L. and S. Aguais, (2019 a), 'Inaccuracies Caused by Hybrid Credit Models and Remedies as Implemented by ZRE', Z-Risk Engine Case Study Research Paper, ZRE web site, September.

Forest, L. and S. Aguais, (2019 b), 'Scenario Models Without Point-in-Time, Market-Value Drivers Understate Cyclical Variations in Wholesale/Commercial Credit Losses, Z-Risk Engine Case Study Research Paper, ZRE web site, June.

Forest, L. and S. Aguais, (2019 c), 'Variance Compression Bias in Expected Credit Loss Estimates Derived from Stress-Test Macroeconomic Scenarios', Z-Risk Engine Case Study Research Paper, ZRE web site, April.

Aguais et al PIT/TTC Ratings, ZRE and Climate Risk Publications

Chawla G., Forest L., and Aguais S. D., (2016), 'Convexity and Correlation Effects in Expected Credit Loss calculations for IFRS9/CECL and Stress Testing', Journal of Risk Management in Financial Institutions, Vol 9/Number 4, Autumn 2016.

Chawla G., Forest L., and Aguais S. D., (2016), 'Some Options for Evaluating Significant Deterioration Under IFRS9', Journal of Risk Model Validation, VOLUME 10, NUMBER 3 (September 2016) PAGES: 69-89.

Chawla G., Forest L., and Aguais S. D., (2016), 'Point-in-time LGD and EAD models for IFRS 9/CECL and stress testing', Journal of Risk Management in Financial Institutions, Volume 9 / Number 3 / Summer 2016, pp. 249-263 (15)

Chawla, G., L. Forest and S. Aguais, (2015), 'AERB: Developing AERB PIT-TTC PD Models Using External CRA Ratings', The Journal of Risk Model Validation: Volume 9/Number 4, Winter 2015, available at: <http://www.risk.net/journal-of-risk-model-validation/technical-paper/2437473/aerb-developingairb-pit-ttc-pd-models-using-external-ratings>

Forest, L., Chawla, G., and, Aguais, S.D. (2015), 'Biased Benchmarks', Journal of Risk Model Validation 9(2), 1–1.

Forest, L., G. Chawla and S. Aguais, (2013/14), 'Comment in response to 'A methodology for point-in-time--through-the-cycle probability of default decomposition in risk classification systems', Journal of Risk Model Validation 7(4), 73-78, Risk Publications.

Aguais, S., L. Forest, M. King, M. C. Lennon and B. Lordkipanidze, (2007), 'Designing and Implementing a Basel II Compliant PIT-TTC Ratings Framework', The Basel Handbook: A Guide for Financial Practitioners, 2nd edition, Ed. M. Ong, 2007, Risk Books.

Aguais, S., L. Forest, E. Wong and D. Diaz-Ledezma, (2004), 'Point-in-Time versus Through-the-Cycle Ratings', The Basel Handbook: A Guide for Financial Practitioners, Ed. M. Ong, Risk Books.

Forest, L. and S. Aguais, S. and D. Rosen, (2001), 'Enterprise Credit Risk', Introduction to, Enterprise Credit Risk Using Mark-to-Future, edited by, S. Aguais and D. Rosen, Algorithmics Pub

Belkin, B., S. Suchower and L. Forest, (1998), 'A one parameter representation of credit risk and transition matrices', Credit-Metrics Monitor, pp.45-56, October.

Belkin, B., S. Suchower and L. Forest, (1998), 'The effect of systematic credit risk on loan portfolios and loan pricing', Credit-Metrics Monitor, pp.17-28, April.