Z-Risk Engine®

Unlocking Credit Cycles

Musings on Long Run Climate Stress Test Modelling for Banks

Presented at: Climate Stress Testing, Marcus Evans, Marriot Hotel, Kensington, London

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Musings on LR Climate Stress Test Modelling

1. Overview:
   a) Key presentation points
   b) 200 Years of 'Carbon Addiction' and 'market failure' have led to the current highly uncertain climate situation
   c) Key Climate Stress Test Drivers
   d) Importance of Climate Structural Change as part of the solution
2. Developing Climate Models Under Substantial Uncertainty:
   a) Overview: Taxonomy for modelling under uncertainty
   b) Benchmarking vs empirical modelling
   c) Examples of 'Risk Modelling' (with empirical data) vs 'Modelling Under Uncertainty'
   d) Need for 'Paradigm Shift' and Inclusion of Potential 'Downside Climate Risks'
   e) Importance of 'Unexpected Systematic Shocks' from aggressive climate carbon policies

Musings on LR Climate Stress Test Modelling cont

3. Key Issues in Developing an Early Climate Stress Test Approach:
   a) High level climate stress test Framework
   b) Notes on Pros and cons of recent climate risk modelling
   c) Current key outstanding research questions for developing a climate stress testing framework
   d) 'Variance Compression Bias' – lessons from traditional stress testing/IFRS9 that use deterministic scenarios
   e) Substantial alterations required to adapt bank Reg Capital stress testing to support climate stress testing
4. Z-Risk Engine Architecture: 'Climate Z' under development - Multi-factor model to be adapted to run deterministic climate scenarios
5. Bibliography
6. Appendix I: ZRE - Developing Deterministic Scenarios vs Unconditional Simulations
7. Appendix II: Early Climate Risk Modelling Summary DRAFT Notes
8. Our Publications: Credit Risk Modelling, PIT/TTC Dual Ratings and Z-Risk Engine

1a: Key Points – Substantial Uncertainty Creates Large Complexity in Developing Climate Stress Test Models for Financial Institutions

- Current climate stress test modelling for banks:
  - V**ery early infancy –** limited **c**urrent research by, Regulators, Asset Managers & Academics
  - Overall modelling effort faces **substantial uncertainty & very limited empirical data**
  - **Consistent Framework for climate stress test modelling not yet well defined**
  - Early climate stress testing effort ***still very valuable to set a solid, consistent Research Foundation***
  - **Data generally available on narrower physical risks:** temperature, CO2, Hurricanes, Wildfires etc
  - **However, climate impact data on broader global climate impacts (transition risk) – in** relation to climate policy changes and financial impacts **not well observed in historical data**

- **Climate credit risk impacts on Banks** – early research suggests limited impacts – further research required plus more general consensus on a general research framework

- **Consensus climate modelling approach not formed yet, but …**
  - Need shorter & longer time horizons – physical & transition risks
  - Forward-looking, scenario-based **deterministic** approaches are most likely modeling candidate
  - **Explicit, forward-looking 'what if' scenarios including unexpected shocks from both** climate policy shocks and market/credit shocks - **explicit narratives required**
  - 200 years of 'carbon market failure' suggests modelling **structural economic change** is a key

1b: 200 Years of 'Carbon Addiction' Requires Substantial Carbon Policy Intervention 'Green Swans' Are Extremely Complex – With Substantial Uncertainty/'Fat Tails'

Climate risks stem from classic market-failure 'writ planetary':

'the aim is to correct [a 200-year] externality using <u>deliberate policy intervention</u> rather than let a more or less evolutionary trajectory guide the transition'.

See Semieniuk et al, (2020), p 5, 'Low-carbon transition risks for finance'.

Bolton et. al., (2020) has characterised climate change as a 'Green Swan':

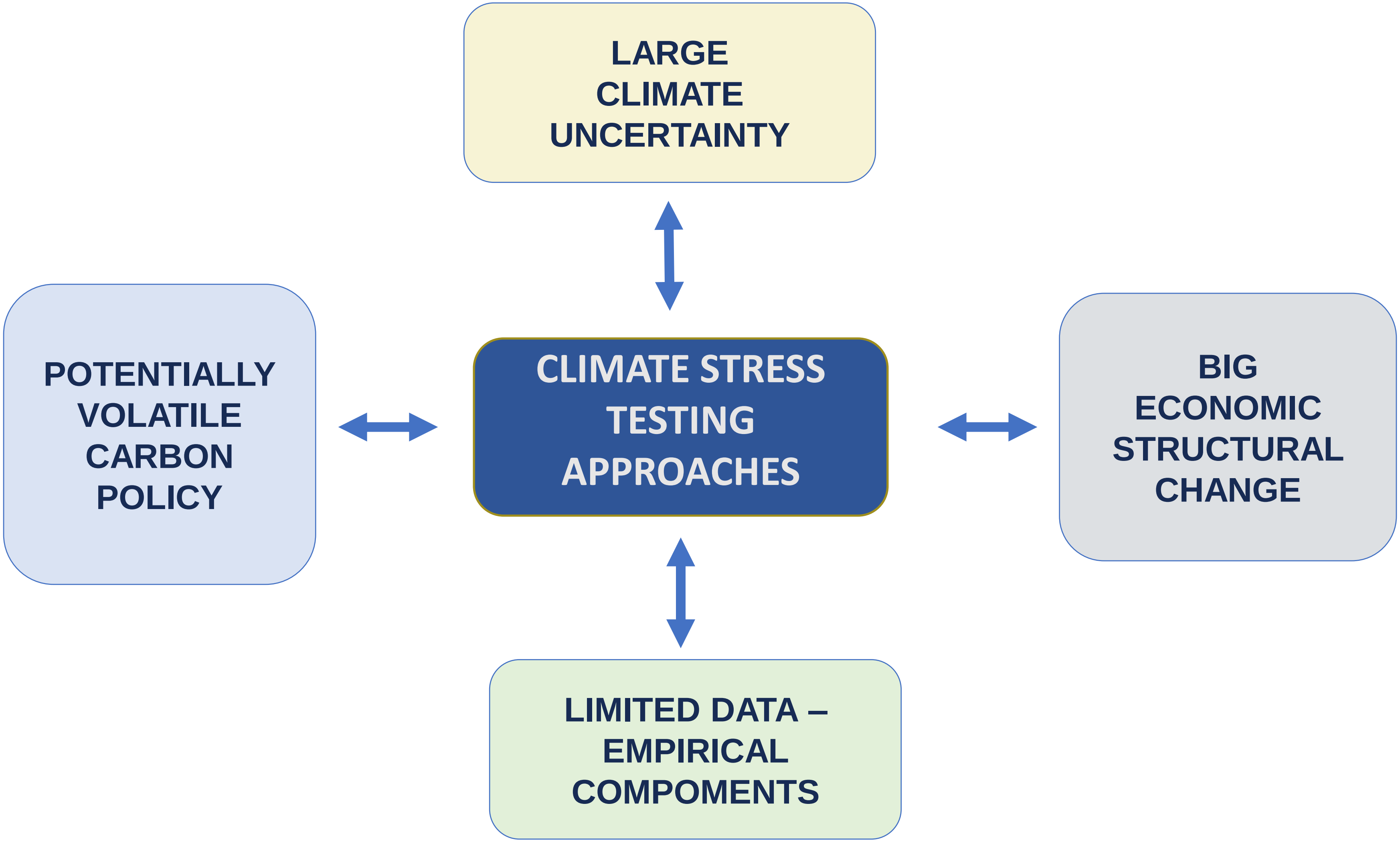
'our framing of the problem is that climate change represents a <u>green swan</u>, it is a new type of systemic risk that involves interacting, nonlinear, fundamentally unpredictable, environmental, social, economic and geopolitical dynamics….climate risks are not just black swans, i.e.., tail risk events,….climate change represents a <u>colossal and potentially irreversible risk of staggering complexity</u>'.

See P. Bolton et. al., (2020), page 6, 'The Green Swan', (BIS/Banque de France)

'Knightian' Uncertainty: '***is a lack of any quantifiable knowledge about possible outcomes and their associated probabilities, as opposed to the presence of quantifiable risk (empirical data)'***

See Knight, F., 'Risk, uncertainty and profit', 1921.

1c: Climate Stress Testing for Banks – Key Drivers



1d: 200 Years of 'Wrong-Way Carbon' Structural Change Suggests **Alternative Structural Change** is a Key Part of Modelling Climate Risk

- Key Paper:
  - *G. Semieniuk et al, (2020) 'Low-carbon transition risks for finance'*
  - Low-carbon transition 'entails large-scale' structural change – asset revaluation shocks, debt default, and the creation of 'bubbles' in rising 'sunrise industries'
  - Rapid, large-scale change (real economy) could substantially impact financial side of the economy
  - Traditional financial 'bubbles/manias' (1929 Crash, radio, airplanes, electricity etc.) usually in sunrise industries
  - Aggressive low-carbon policy shocks to 'sunset industries' would be a new risk phenomenon
  - Substantial stranding of carbon assets, carbon capital equipment can create substantial 'sunset' financial risks

- Other key academic papers:
  - *T. Ciarli & M. Savona, (2019) 'Modelling the Evolution of Structure and Climate Change: A Review'*
  - Review of various developing models for Climate Risk and interrelationships between the environment & the economy

- Projected Carbon Asset Stranding (general estimates):
  - **33% of oil reserves**
  - **50% of natural gas reserves**
  - **80% of coal reserves**

2a: Taxonomy for Modelling Under Substantial Uncertainty - Estimating Possible Outcomes & Relevant Empirical Probabilities **Not Straight-Forward**

<u>RISK MODELS</u> USUALLY COMBINE KNOWLEDGE ON OBSERVED OUTCOMES TO EMPIRICALLY ESTIMATE PREDICTED OUTCOMES – BUT LARGE UNCERTAINTY MOTIVATES SCENARIO-BASED APPROACH WHEN EMPIRICS DOESN'T WORK WELL

'THE WORLD IS MOSTLY GRAY'

100% CERTAINTY

100% UNCERTAINTY

RANDOM/STOCHASTIC PROCESSES

DETERMINISTIC

'Everything in state of flux'
'Predictions are impossible'

'KNOW SOMETHING BUT UNCERTAINTY IS HIGH'

RUMSFELD

KNOWN KNOWNS* | **KNOWN UNKNOWNS** **?**

'DON'T KNOW BUT UNDERSTAND GENERALLY'

? **UNKNOWN KNOWNS**

? **UNKNOWN UNKNOWNS**

BLACK SWANS

SUPORTABLE EMPIRICAL APPROACHS TO RISK MODELLING

KAY/KING

'RESOLVABLE UNCERTAINTY'** **?**

? **'RADICAL UNCERTAINTY'**

EMPIRCAL DATA DOESN'T SUPPORT 'REASONABLE' PROBABILITY ESTIMATION OF OUTCOMES

'MODELLABLE RISKS' ??

CLIMATE UNCERTAINTY ??

*Adapted from D. Rumsfeld, 2002, Notes from press briefing.
** 'Radical Uncertainty', (2020) J. Kay & M. King

2b: Taxonomy for Modelling Under Substantial Uncertainty – **Benchmarking vs Empirical Modelling** – Unexpected Regional Population Migration 'Shock'

SCIENCE VS ART'

"EMPRICAL MODEL DEVELOPMENT vs 'BENCHMARKING' vs WINGING IT'

ABUNDANCE OF EMPRICAL DATA ⟷ **ZERO EMPIRCAL DATA**

RANDOM/STOCHASTIC PROCESSES

'EMPIRICAL MODELS' | **'BENCH MARKING'** | **"FOUNDATIONAL NARRITIVES'** | **'STRUCTURED WORDS'** | **'JUST WORDS'**

'LOGICAL STORY BASED UPON FOUNDATIONAL ECONOMIC MODEL'

'BENHCMAKING INVOLVES USING SIMILAR OBSERVED HISTORICAL OUTCOMES TO IMPLY ALTERNATIVE HYPOTHETICAL IMPACT'

PROXING CLIMATE POIPULATION MIGRATION SHOCK

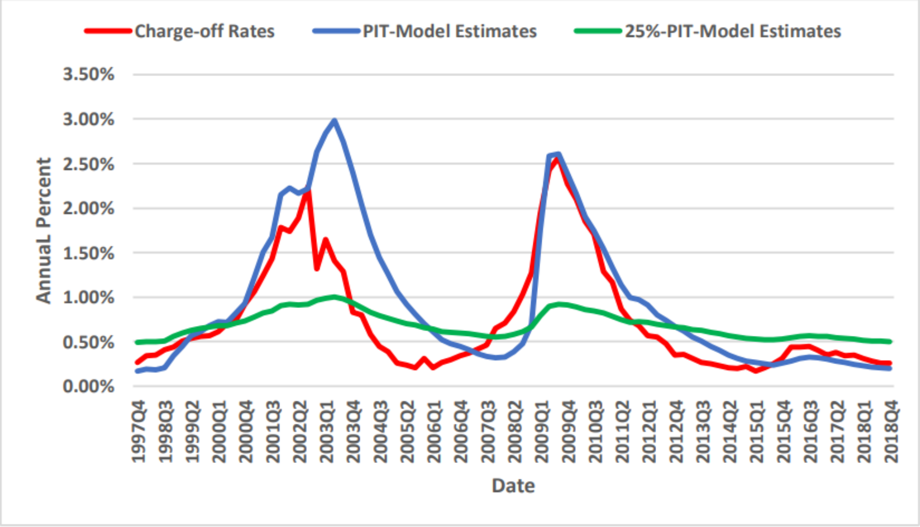
HYPOTHETICAL CLIMATE/SOCIAL MIGRATION – AFRICA TO EUROPE

- Largest observed historical population migration 'shock' – WW2 – 50 million people
- Africa population now – 1.2 bil
- Europe population in 1945 – 525 million
- Europe population now – 745 million
- Re-scale WW2 migration 'shock' to current time – implies same 'shock' would be 70 million people 'migrating' to Europe – almost 10% upward shock to Europe population
- **2X WW2 shock – 140 million people**
- ***3X WW2 shock – 210 million or nearly 30% population increase !!!!***
- ***NEED A FRAMEWORK THEN FOR TRANSLATING HYPOTHETICAL CLIMATE SHOCK TO CLIMATE IMPACTS***

2c: Example of 'Risk Modelling' vs 'Modelling Under Uncertainty' - Empirical Risk Model for Credit Cycles vs Potential Future Climate Impacts

Risk Model Example: Predicting Systematic Credit Cycle Impact on Large Corporate Default Rates

- Detailed Loss & Credit Cycle fluctuations are **Observable**
- Well specified, **statistically significant 'risk models'** can be estimated
- Z credit cycle models convert TTC IRB PD models to PIT (**BLUE PIT**) roughly DOUBLING statistical fit of IRB PD Models (GREEN TTC) to improve prediction of observed credit losses (RED)

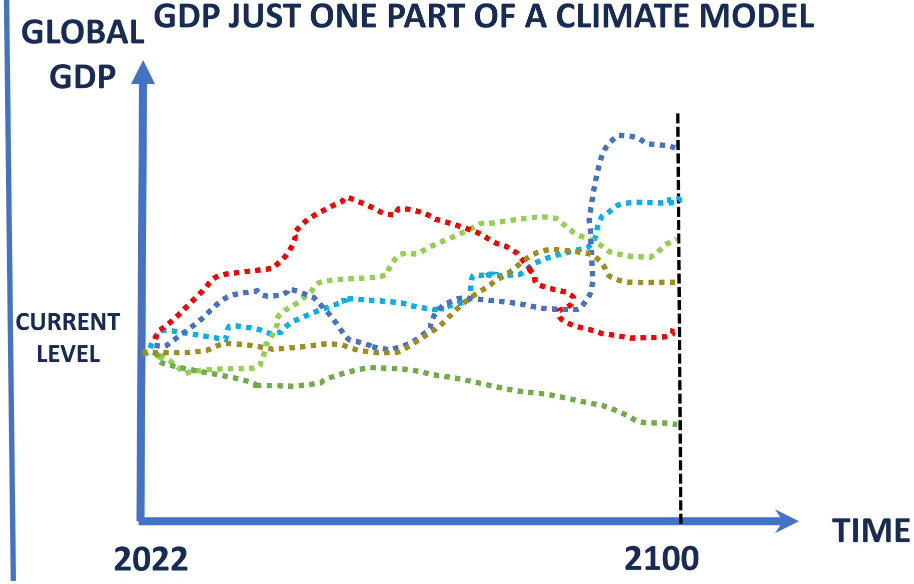


Back Tests Over 1997Q4-2018Q4 Comparing PIT- and Hybrid-Model Estimates With Actual Values of US-Bank, C&I Charge-Off Rates; *Source: Author's calculations using the ZRE Application, Moody's CreditEdge data, and US Federal Reserve data at* https://www.federalreserve.gov/releases/chargeoff/chgallsa.htm

Climate Uncertainty Example: 'Known Unknowns' Future Possible Global GDP Paths

- Alternatively, **Climate Impacts are a 'Known Unknown'** which are broadly understood, but hard to empirically model due to substantial uncertainty
- Narrow physical impacts observed to-date, but broader economic impacts counting explicit climate not observed
- Therefore need structured, scenario/narrative approach to derive Hypothetical future GDP paths and climate impacts under different climate scenarios

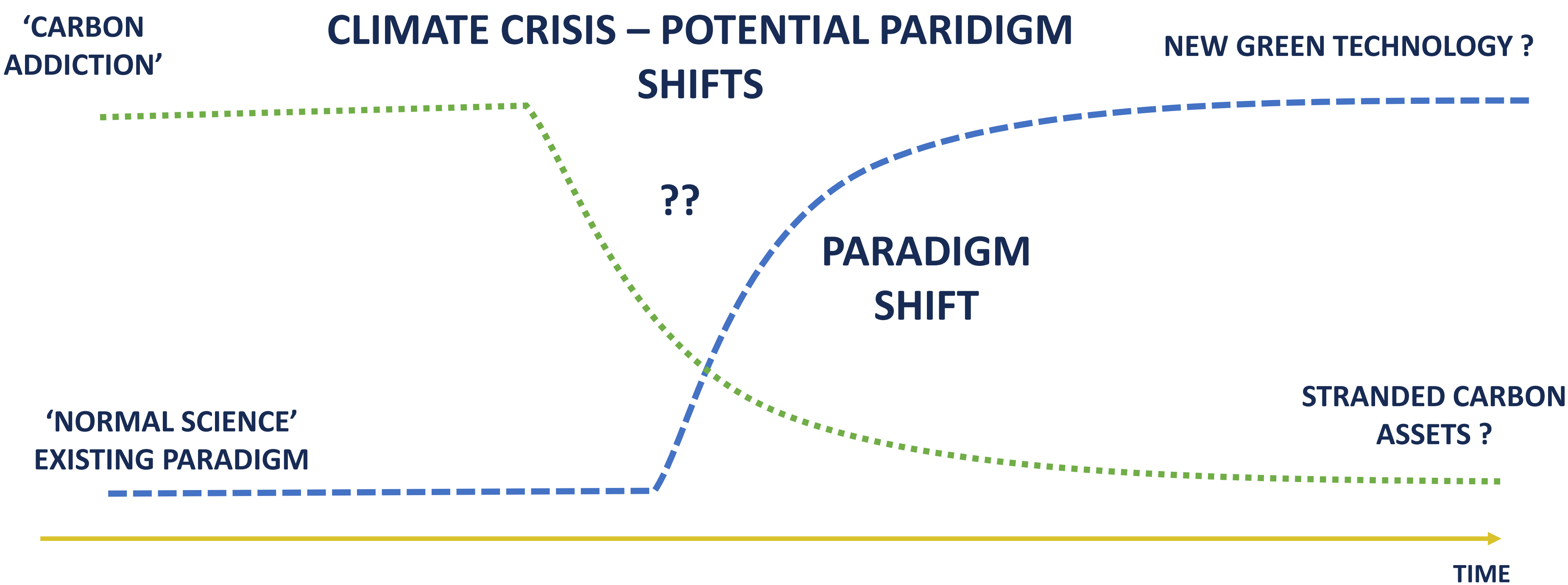
EXAMPLE: FUTURE POTENTIAL GDP PATHS
GDP JUST ONE PART OF A CLIMATE MODEL



2d: Thomas Kuhn, ‘The Structure of Scientific Revolutions’ (1962)
Science Evolves In ‘Jumps’ – Not Continuous Cycle of Smaller Improvements

‘Epistemological Break Suggested as Key’

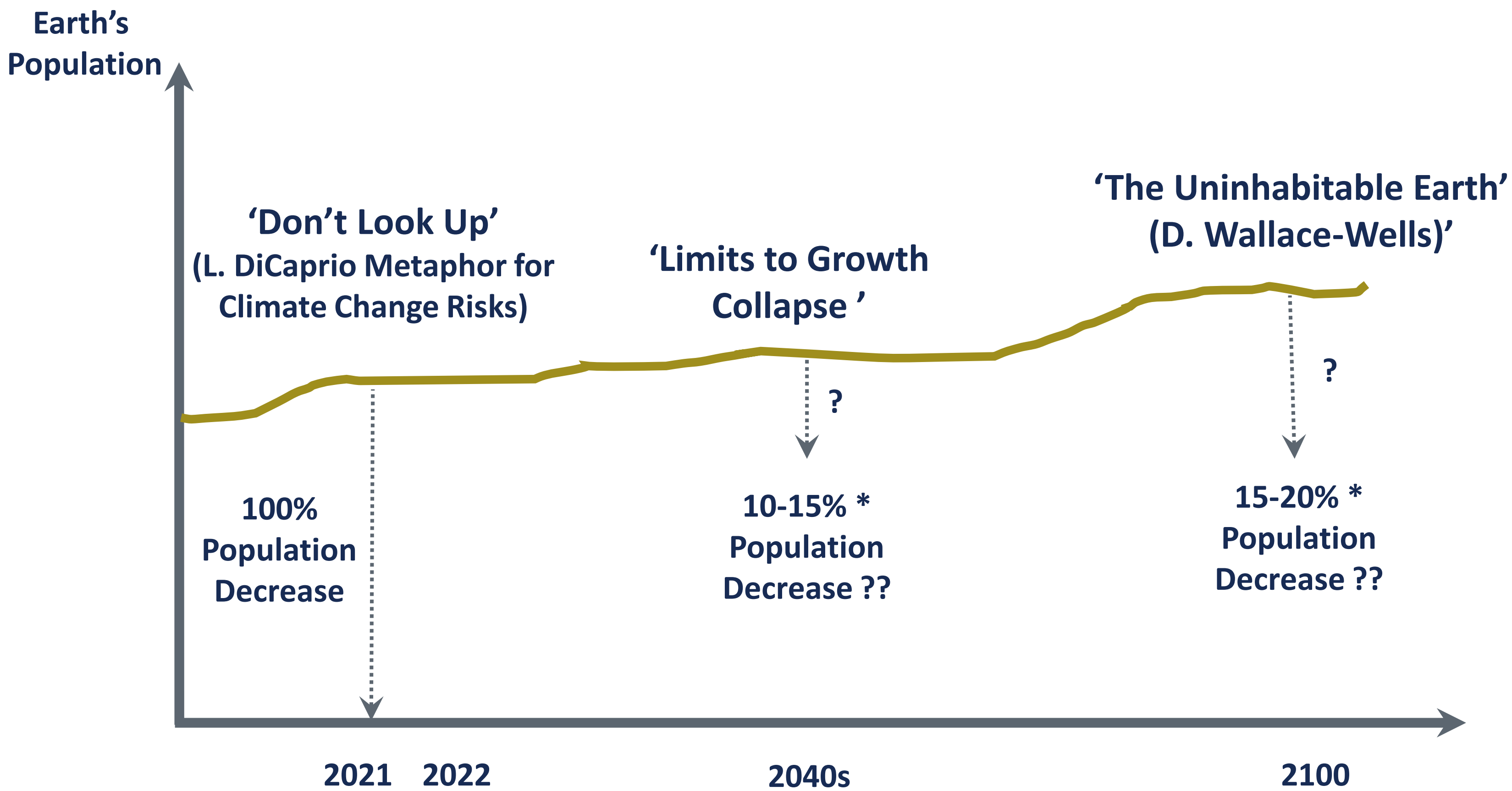
- *‘Scientific progress requires radical breaks from previous ideological conceptions’*
- Forward not Backward Looking
- Minimal Historical Data for model estimation
- ‘Structured mixed model’
- Very short & long run horizons to 2100 ?



2d: Climate Change Uncertainty is Massive – How Bad is the 'Potential Downside Risk' Wagner/Weitzman Estimate 'Tail Risk' of Potentially Exceeding +6 C at Roughly 10%

Climate Change Risk 'Hypothetical Downside Risks'

THIS IS NOT A 'DOOMSDAY FAIT ACCOMPLI PROJECTION' – THESE EXAMPLES SIMPLY ILLUSTRATE THE NEED FOR INCLUDING 'POTENTIALLY EXTREME NARRATIVES'



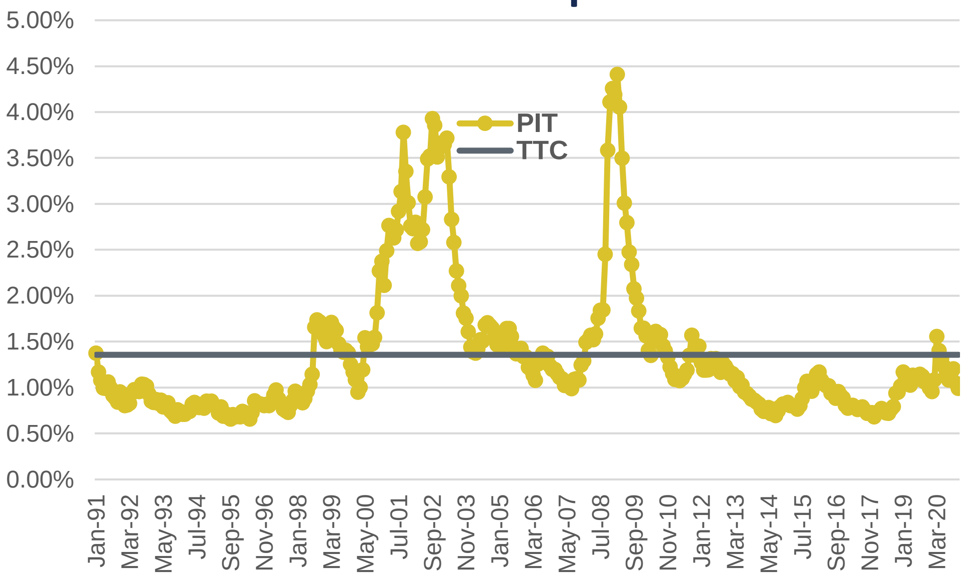
* '100% Illustrative SWAG Guesstimates'

2e: In Risk Models & Climate Modelling Under Uncertainty - Systematic Unexpected Shocks Drive Potential Future Real/Financial Volatility

Unexpected Credit Risk Shocks Substantially Boosted Observed PIT PDs During the Last 2 Credit Cycles

Unexpected Shocks Drive Systematic Risk

TTC As An Average of PIT Calculated PDs – NA Corporates*



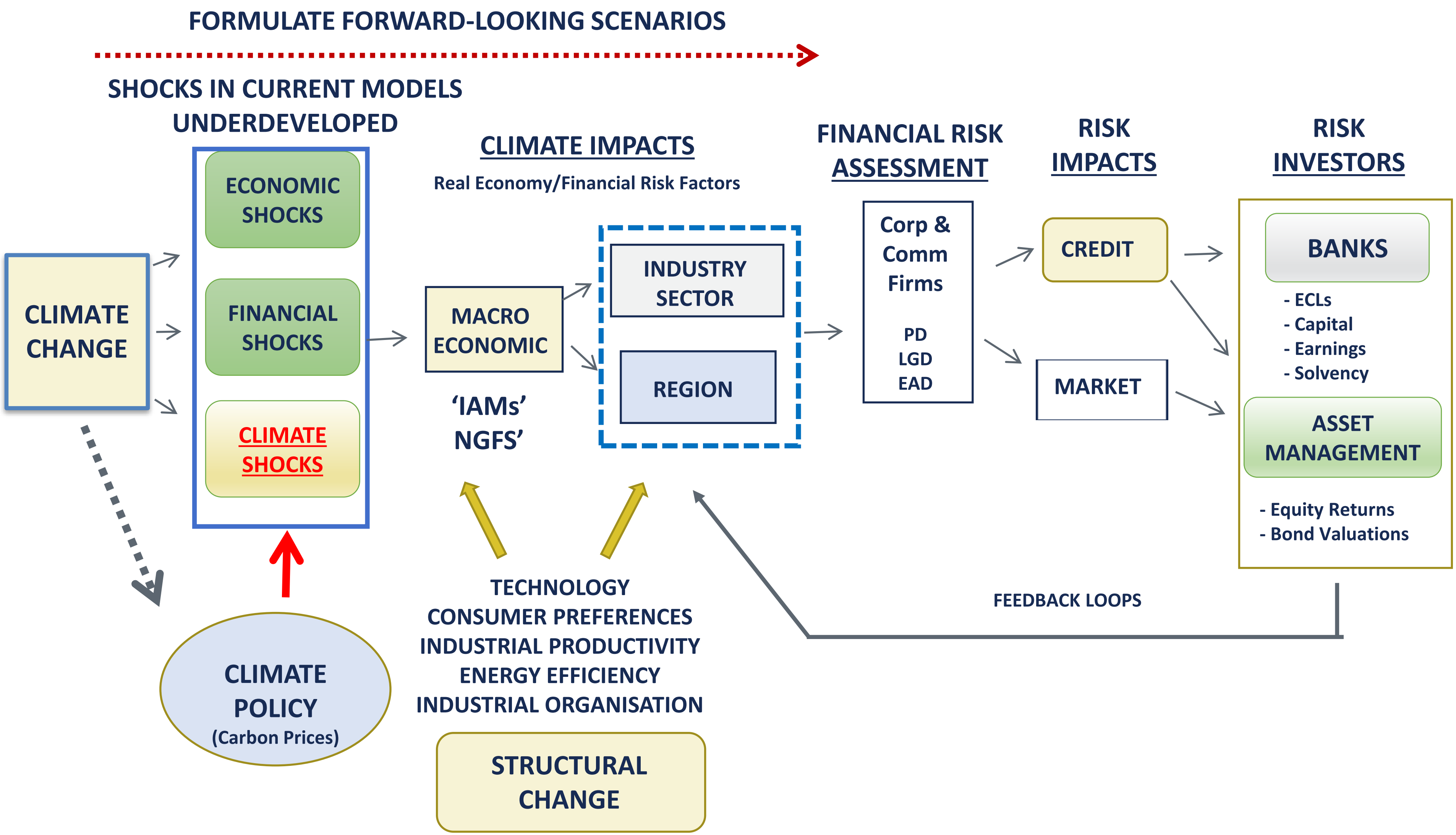
*Derived from Z-Risk Engine and Moody's CreditEdge EDFs

Much of Current Climate Modelling is Driven by Future 'Unexpected' Climate Policy Shocks

Sudden, Unplanned Climate Policy Shocks are Key to Potential Future Negative Impacts
Climate Policy Shocks Coupled With Other Economic/Political/Social/Credit Shocks Create Even Greater Future Risks

- **Examples of Climate 'Shocks' Utilized in Recent Climate Change Modelling:**
  - **2015 Paris Agreement as 'policy shock'**
  - **100% fossil fuel Equity value drop shock**
  - **Bond value shocks – difference between adverse and very adverse climate scenarios**
  - **Various deterministic carbon price shocks (e.g., + $100-300 increases in carbon prices)**

3a: Modelling Climate Risk – Stress Tests With Forward-Looking Scenarios – Volatile Climate Change POLICY Produces Unexpected Shocks Shocks



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3b: Draft Notes: Pros and Cons of Some Recent Climate Models/Studies

Study'	Description	Pros	CONS
ECB Stress Test	• Firm level projections of financial results net of damages enter into financial ratio model of default	• Logical financial ratio model of defaults.	• Cross-sectional estimates of cost, revenue and asset equations appear to be done separately, not jointly, • Default model involves only book-value financial ratios • Only a few, deterministic scenarios not enough to indicate range of risks • Impacts depend on artifice of incomplete carbon price passthroughs
S&P (Baldassarri et al)	• Projects firm-level EBITDA as influenced by carbon price changes, • Uses industry median asset value to EBITDA ratios in deriving asset values • Enters asset values as other variables into Merton PD model	• Merton framework using market leverage measures	• Impacts depend on artifice of incomplete carbon price passthroughs • Holds volatility and returns fixed
'CERM'* (Green RWA)	• Introduces climate risk factors on top of 'economic' ones into longstanding simulation framework	• Allows for many climate-related scenarios • Acknowledges that climate and other risks may occur as unexpected shocks.	• Relies on many hard-to-estimate parameters. • Appears to rely on Gaussian distributions, without fat-tail effects. • Underlying structural model not shown.
Stern, Stiglitz, Taylor	• Criticizes IAM modeling • Proposes instead cost-effectiveness analyses of policies for achieving the Paris Accord targets	• Not just a critique in offering an alternative to IAM approaches.	• Guidance rather opaque

* The 'CERM' or, 'Climate Extended Risk Model', uses the general, multi-factor and conditional credit Transition Model approach used in Z-Risk Engine.

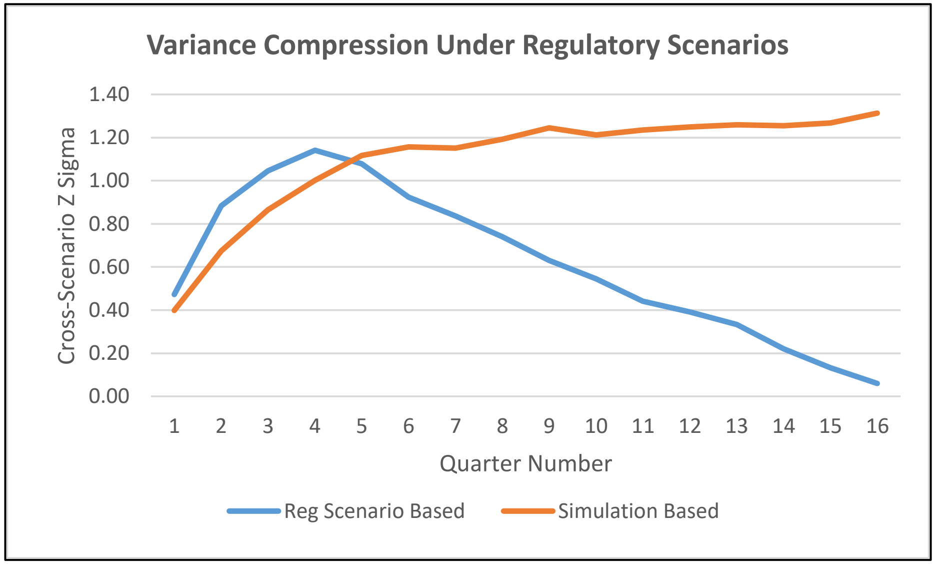
3c: Some Outstanding Questions in Developing A Climate Stress Test Research Framework

- Scenario Generation: Deterministic vs Simulated:
  - 90% of banks use deterministic scenarios for IFRS9 & Stress Testing
  - Climate Stress Test Approaches To-Date – Limited (3-4) Deterministic scenarios (NGFS) dominate
- ‘Variance Compression Bias’ – using a deterministic scenario approach most likely requires a larger number of scenarios
- Uncertainty - Biased vs Unbiased Scenarios - Stern-Stiglitz/Di Caprio:
  - Current limited climate scenarios probably don’t achieve ‘unbiased’ results
  - Stern-Stiglitz: Including a ‘catastrophe’ scenario leads to an undefined/infinite result
  - Exclude extreme Di Caprio scenario for Tractability – but need approach for generating potential, reasonable, ‘short of catastrophe’ scenarios
  - Underlying theoretical probability distribution most likely requires a ‘Fat Tail’ Distribution
- Linking Scenario Narratives/Partial Data/Benchmarking (Real World Stress Test Group)
- Capability to run standardized (NGFS) scenarios & customized scenarios plus explicit carbon policy impacts

3d: Variance Compression Bias: IFRS9 Example - Limited Deterministic Scenarios Leads to Reduced Future Variability Compared to Simulated Scenarios

- Need large numbers of probabilistic scenarios to describe the future distributions of credit conditions including the possibility of recession at any time

- Handful of regulatory or ICAAP scenario designed to test the adequacy of current capital resources, front load variations (recession) 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.

3e: Extending Traditional Capital Stress Testing vs Establishing a Revised, Broader Uncertainty-Based Stress Test Approach

Current 'Traditional' Stress/Risk Modelling for Climate In Its Infancy*

- Mainly NGFS-Centric scenarios
- Scenarios tend to be too 'smooth'
- IAMs imply limited macro impacts
- 'Unexpected shocks' approach still under discussion & application
- Observed historical climate impact in macro & financial data very limited at best
- Designed as preliminary extensions of Reg Capital Stress Tests
- Very limited representation of climate policy, economic structural change or systematic credit cycles

Broader Uncertainty-Based Scenario/Narrative Approaches Most Likely a Requirement *

- Neural-Centric Bias potentially considered
- Kuhn implied 'revolution in approach'
- Major Economic Structural Change key (I/O)
- Non-Linear, endogeneity, tipping points, social/political/credit shocks are important
- Most likely utilize larger range of deterministic scenarios with detailed narratives
- Apply empirical data where possible (assessing emissions intensity, I/O to facilitate Scope 1/2/3)
- Systematic, multi-factor models for adapting credit models already fairly well specified
- Unexpected policy shocks drive uncertainty in conjunction with other unexpected systematic shocks
- Account for Variance Compression Bias & 'extreme' scenarios but tractable math

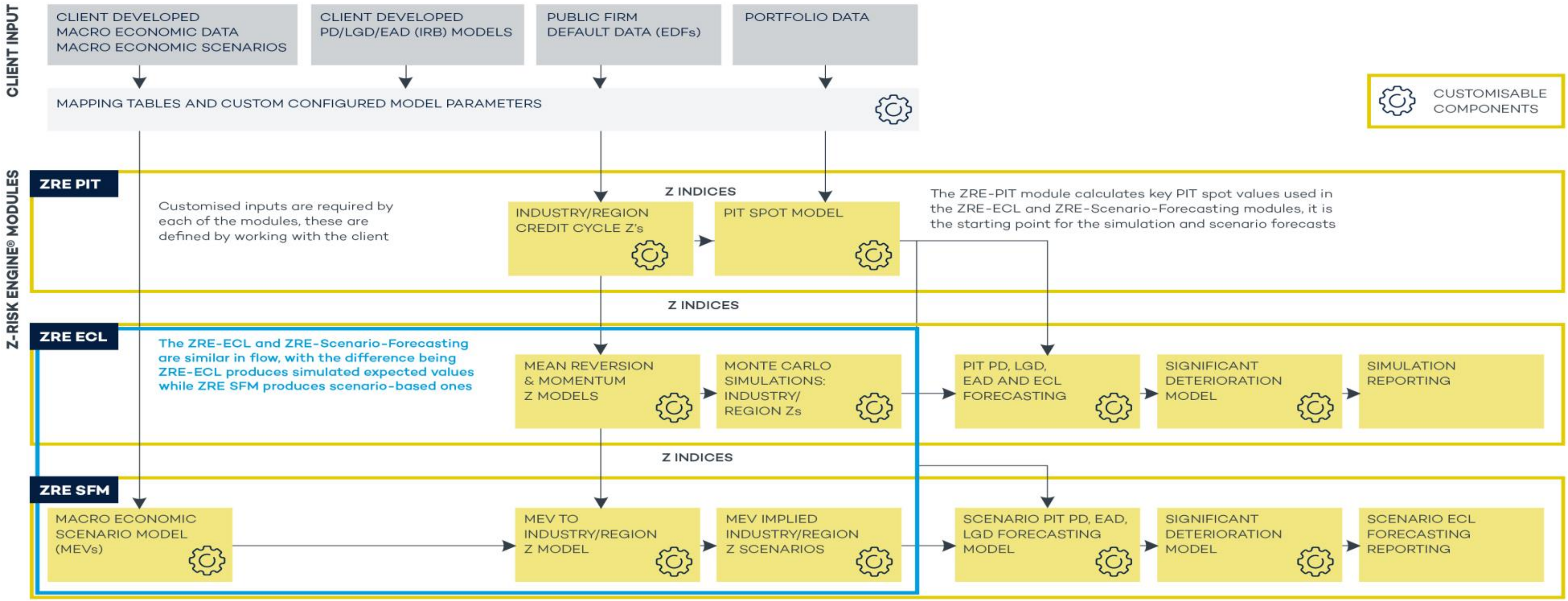
*See, M. Cliffe, 'Stressful Tests', Environmental Affairs, WWW.POLICYEXCHANGE.ORG.UK.

4: Current ZRE Solution in Python for IFRS9/Stress Testing Can Also Support Climate Stress Testing - Using Multi-Factor Systematic Risk Framework and Deterministic Scenarios

- **Multi-factor approach already projects IFRS9 ECLs using either of two approaches:**

  1. **Deterministic MEV Scenarios: Assess ECLs using MEV scenarios with systematic Z factors**
  2. **Or, simulation-based Z credit factor approach: industry/region second-order Z credit cycle factors**

- **Plan: add detailed Climate Z using scenario approach**



Key Points – Impact of Uncertainty on Climate Stress Test Modelling for Banks is Substantial

- **Modelling complexity**: Developing Climate Models when **Substantial Uncertainty** exists with limited observed historical data
- Climate stress test modelling for banks – **in its infancy –** but it's key for the industry **to agree an overall consistent, Research Foundational 'Framework'**
- Climate data from history is available in more detail for physical & narrower climate impact modelling but **probably not** for broader macro assessments as **major climate policies & structural change haven't occurred**
- Consensus to-date: **climate impacts show limited bank risk impacts –** further research required
- **Consensus** climate modelling approach **not formed yet**, but is under discussion focused most likely on a **forward-looking, scenario-based** framework with explicit narratives due to substantial uncertainty
- **Unexpected shocks**, most likely driven by future **climate policies implemented** on top of other **market/credit systematic shocks** observable in the past & modelled in Z credit factors provides one possible solution

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6: Appendix I: Deterministic Conditional Scenarios vs Unconditional Simulations

- In this Appendix I, we highlight key issues surrounding running conditional, deterministic scenarios vs running unconditional scenarios using a simulation model

- To support this discussion, we use the Z-Risk Engine solution which runs both types of risk assessment for IFRS9 & current Stress Testing:

  - ZRE uses deterministic MEVs and sector/region credit cycle models to assess IFRS9 ECLs, or, regulatory capital stress tests, or,

  - ZRE runs unconditional simulations through industry/region credit cycle models to project ECLs

6: Appendix I: Deterministic Conditional Scenarios vs Unconditional Simulations

CONDITIONAL - typically refers to a **user based prediction** of the future where value or distribution of a variable is derived based on user's judgement.

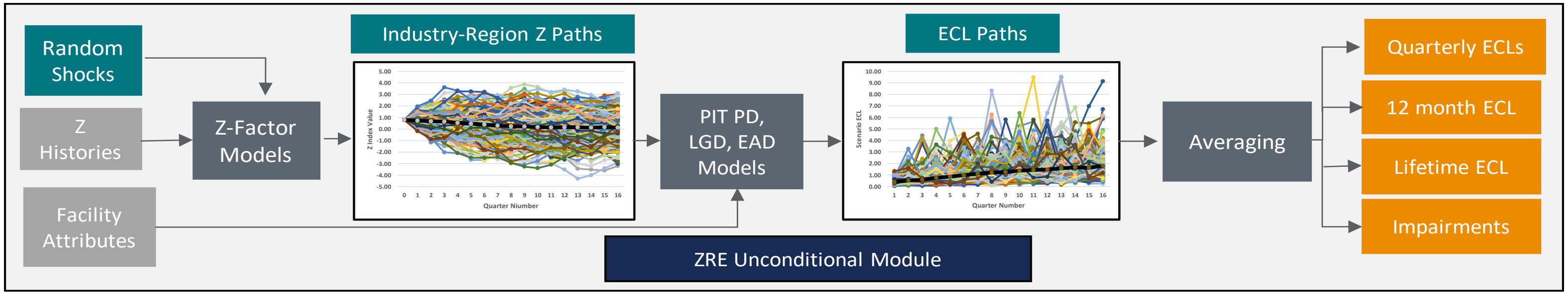
UNCONDITIONAL model based prediction of the future **nothing arbitrary is assumed** about the future. Model uses **historical data to predict possible future outcomes**, assigns probabilities weights & ensures unbiased nature of variables and hence outcomes.

UNCONDITIONAL ZRE ECL APPROACH = MORE SIMULATED SCENARIOS WITH BETTER ETIMATED PROBABLILITY WEIGHTS

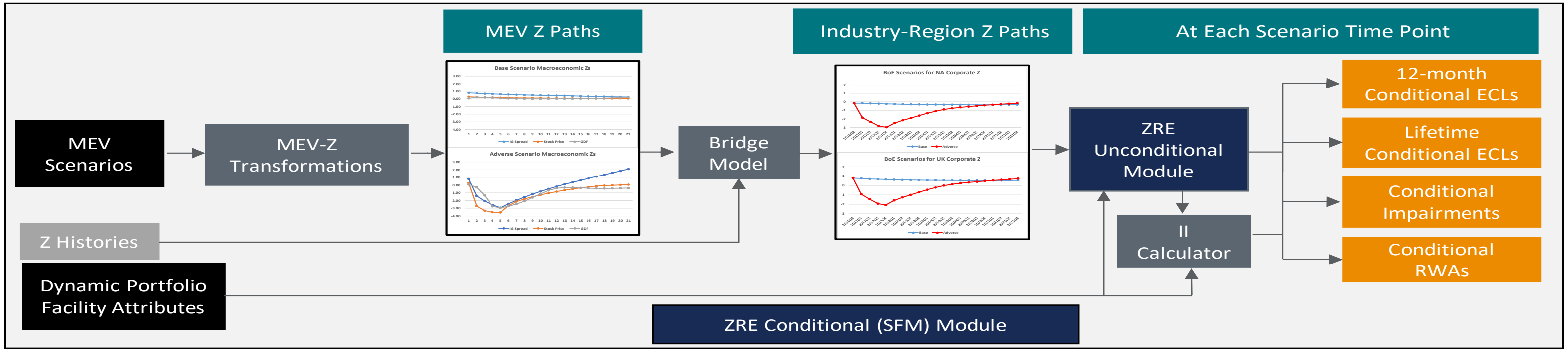
Features / Benefits	CONDITIONAL	UNCONDITIONAL
Definition	Experts design scenarios, assign probabilities, weights. Macro factors used as inputs to models	**Model uses historical data to predict possible future outcomes, assigns probabilities weights**
Understanding of current credit and macro economic conditions	**Subjective**. Differences across industry/regional credit conditions are expert based. Experts quantify all starting points across industry/regions	Long run historical data and informs us on credit conditions.
Forward looking element of macro variables	**Subjective** based on economist's or regulator's views e.g. GDP up 2%, LIBOR up 1%, agnostic to historical data	Forecasting model built on historical data informs forward looking element.
Unbiased element of forecasts	Experts have to sign off on overall scenarios being unbiased. Bias in scenarios can lead to high/low provisions and income smoothing. **Regulators typically don't provide upside scenarios**	**Range of forecasts with probabilities provide an unbiased view of forecast**
Probability weighting of macro variable forecasts	**Subjective based on probabilities assigned by economist. Regulators typically don't provide probability weights. Humans typically cannot provide accurate probabilities to extreme events e.g. probability of less than 0.5% and in multi-dimensional space**	Probabilities provided by forecasting model (Macro Monte Carlo or Z Monte Carlo)

6: Appendix I: A ZRE Example Approach to Supporting IFRS9 & Stress Testing

- ***Unconditional***, for ECL provisioning, which involves generating a large number of statistical scenarios representative of all possible, future credit states and forming an average of the related, ECL scenarios

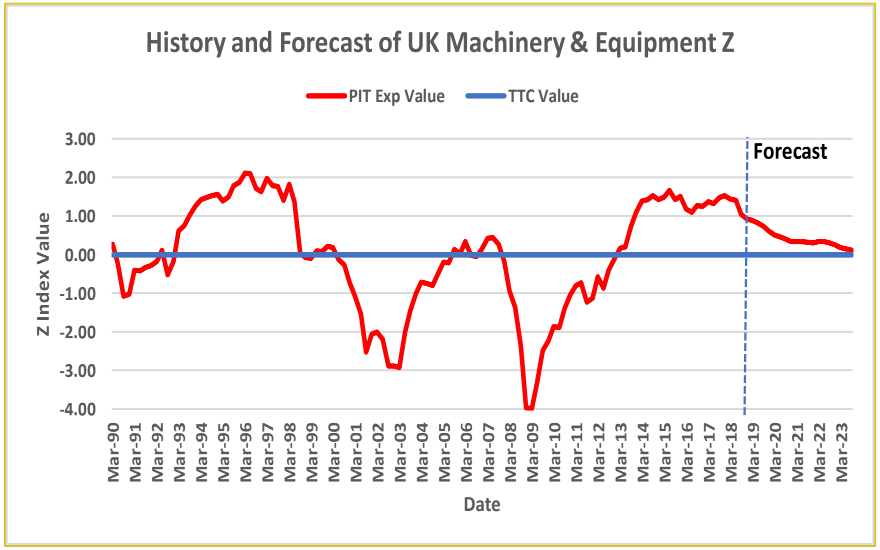


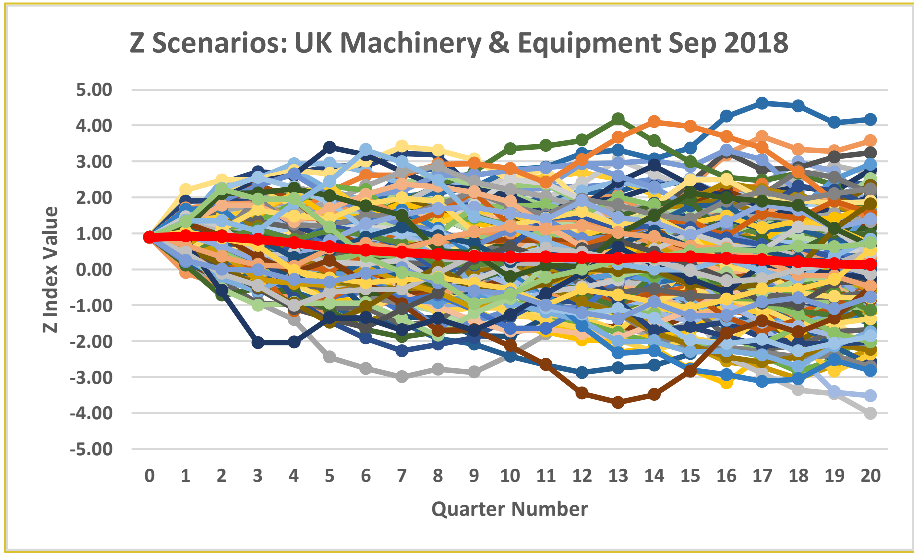
- ***Conditional***, for stress testing, which involves determining the ECL paths implied by baseline and stress, macroeconomic assumptions



6: Appendix I: ZRE ECL Unconditional Simulation Estimates Involve Many Credit-Cycle Scenarios

UK, machinery-&-equipment, Z scenarios start at the Sep 2018 value of about one annual standard deviation above average and exhibit mean reversion and rising variance over time; Z levels early on reflect current conditions and the many scenarios produce averages that account for the skewness of each quarter's loss distribution

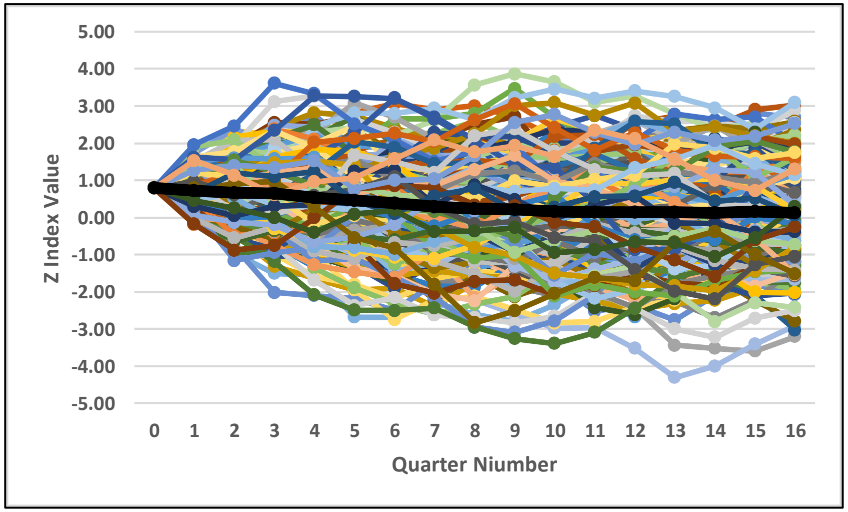


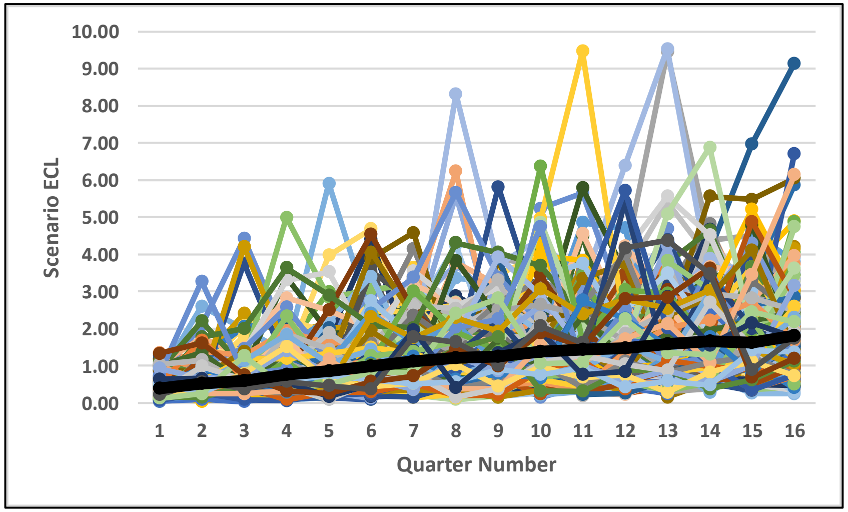


Source: ZRE application drawing on Moody's CreditEdge EDFs

6: Appendix I: ZRE Unconditional Simulation Scenario Generation

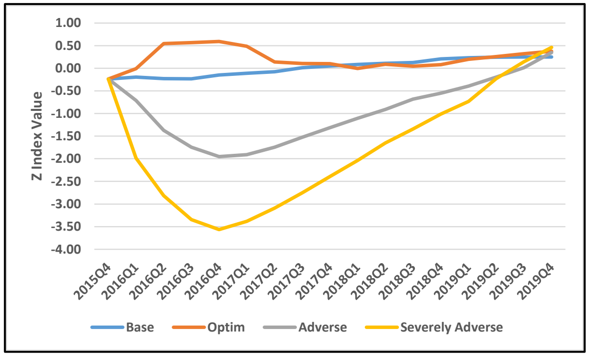
- Enter initial conditions (current and past Z values) and random shocks into the Z credit cycle models and produce Z scenarios
- Feed the Z scenarios into the PIT PD, LGD, and EAD models and thereby produce ECL (= ΔPD x ELGD x EEAD) scenarios
- Average the ECL scenarios and obtain estimates of unconditional, ECL term structures

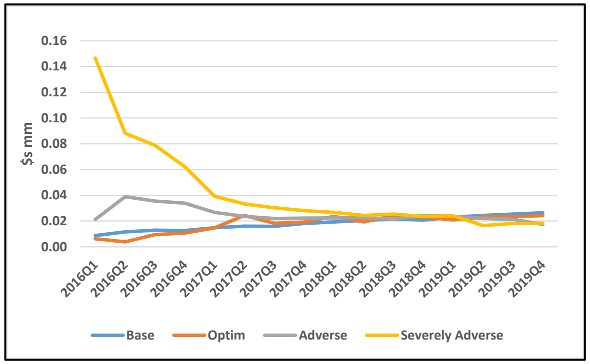




6: Appendix I: ZRE Conditional Module Scenario Generation

- Start with predetermined, MEV scenarios and transform selected MEVs into MEV Zs
- Enter those MEV Zs along with past values of industry and region Zs into a bridge model and obtain industry and region Z scenarios
- Enter the industry-region Z scenarios into the PIT PD, LGD, and EAD models and obtain the related ECL scenarios





As with PD models, to obtain PIT outputs, the selected MEVs must include market-value indicators. GDP alone understates cyclical variations.

7: Appendix II: Climate Risk Modelling Summary DRAFT Notes

	ECB	Baldassarri et al (2020)
APPROACH	• Credit Risk • Top-Down & Bottom-Up • Physical (primary) & Transition Risk • 4 mil firms assessed • Uses NGFS Scenarios • Emissions for Scope 1, 2 & 3 • 30-year horizon primarily • Derives firm and sector specific PDs	• Credit Risk • 3 key carbon price scenarios • 30-Year Horizon to 2050 • S&P Merton PD Model (PDMS) DD • 'Carbon Price Risk Premium' for Scope 1 & Scope 2 • Carbon price scenarios impact firm costs with various price elasticity assumptions sector on possible cost pass-through
SCOPE/DATA	• 1600 Euro Banks included • Multiple public & private data sets used • Probably most extensive top-down & granular 4 mil firms climate stress conducted to-date • Some data sources: Urgentem scope 1-3 methodology • Four Twenty Seven – for physical & specific location risk	• Emissions data source: TruCost • 'Carbon Intensity': Carbon Emissions per $ firm revenue • 739 firms with $1bil used for emissions data aggregated to sector • Fast Transition 7X carbon prices to 2030 at $120 in OECD
IMPACTS	• 'High risk' corp portfolios see roughly 30% rise in average PDs • 'Low-Risk' firms see smaller PD increases	• Aggregate public company PDs rise across the board • Utilities, martials, energy and consumer staples sectors present the highest default rates

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7: Appendix II: Climate Modelling Summary DRAFT Notes

	Dutch National Bank	Banc de France
APPROACH	• Vermuelen et al (2019, 2021) • Top-down stress test + sector details • Carbon price + technology shocks by sector • 5-Year Horizon • Derive 'TVF' – Transition Vulnerability Factor – Beta Scale Factor • Credit Risk + Market Risk • Equity return drops trigger credit rating notch downgrades	• Credit risk – stress test • IAM/NGFS/NiGEM/Sector/Firm Rating Model • 2020-2050 horizon • Carbon prices shocks 2030/2035 • Sector model uses 'production networks' and I/O model • Static multi-country, multi-sector General Equilibrium
SCOPE/DATA	• Aggregate Dutch banking system • 80 Banks, Insurers + Pension Funds • EXIOBase Emissions + I/O VA Data • 56 Industry Sectors	• About 15 key macro-economic variables • 56 Industry Sectors • France/Rest oif EU/US/Rest of World
IMPACTS	• Up to 11% portfolio value drop • Up to 4.3% CET drop compared to roughly similar capital impacts from recent stress test • 'Sizable impacts but Manageable'	• Largest PD increases on order of +500 bps • Largest sector VA declines of 20-40% roughly • Largest GDP decline for France of about 5-6% in adverse scenario to baseline

7: Appendix II: Climate Risk Modelling Summary DRAFT Notes

	Bouchet et al (2020)	Adenot et al (2022)
APPROACH	• Credit Risk (debt) focus • 5-Year & 40-Year Horizons (2060) • Range of IPCC Carbon Price Scenarios with increases in the $200-700 range • Credit Risk PD Changes from EBITDA Impacts on Firm Cash-Flows • No 'Adaptation' or technology changes assumed	• 'Cascading Carbon Price Effects Through Value Chain & Individual Firms' • Focus on Cross-Sector diffusion of carbon price shocks using I/O global cross-country model • Utilizes • 40-Year Horizon to 2060 • $50, $100 & $300 carbon price shocks consistent with other 2030/2040 carbon price scenarios • EBITDA shocks from carbon price scenarios applied direct/indirect
SCOPE/DATA	• MSCI World Index 1644 start data • 795 Large-Mid Corps in 23 countries with Scope 1 Data • Emissions Data: Carbon Disclosure Project (CDP), TruCost (Benchmarking)	• MSCI World Index 1552 firms across 23 countries • WIOD – World I/O Database
IMPACTS	• Biggest sector impacts on Utilities, Materials & Energy Sectors • 40 Year Cumulative PD Impacts above 'Carbon Price Threshold' at roughly 75%	• Worst case shock impact up to 47% enrings reduction in Utilities • Less carbon intensive Information Technology sector suffers up to 23% earnings reduction

7: Appendix II: Climate Risk Modelling Summary DRAFT Notes

	Battiston et al (2017)	Monasterolo – CLIMAFIN (2019)
APPROACH	• Equities & debt stress tests • 'Network approach' to interdependent financial system risks – looks at direct & indirect effects • Focus Banking systemic losses both direct and indirect using 'Climate VaR' • Primary shocks defined as climate-relevant firms losing 100% of their equity • Banking debt impacts flow from equity shocks	• Financial stress test framework – IAM macro shocks defined as differences between 'adverse' & 'very adverse' climate scenarios • Shocks impact Risk-Neutral PDs on financial contracts (Sov Bonds) – Climate VaR • One version assesses Defaultable Sovereign Bonds – direct & indirect effects
SCOPE/DATA	• Euro & USA listed firms – roughly 15k firms & 65k shareholders • Array firms/shareholders by 'climate relevant' sectors • Includes analysis of top 50 EU Banks	• LIMITS Scenario data – Global CO_2 Emissions • 'CPRS' 'Climate Relevant Policy Sectors' includes Fossil fuel, utilities, energy-intensive, housing & transport • Major bank equity exposures
IMPACTS	• Direct effects not that big, indirect effects large • 'Portion of bank's loan portfolios exposed to 'climate relevant sectors' is roughly equal to bank's capital' (Battiston 2017, p283)	

7: Appendix II: Climate Risk Modelling Summary DRAFT Notes

	Reinders et al (2020)	Capasso et al (2020)
APPROACH	• Finance 'valuation' approach + Merton • Aggregate industry focus • Carbon price asset value shocks coupled with pass-through assumptions of zero & 50% • EU100 & EU200 carbon price shocks • Overnight and phased in price shocks • Horizon unclear…2050 ?	• Uses Merton DD approach to assess climate change & firm credit risk • High 'climate footprints'' or 'climate intensity' cet par increases credit risk (PDs) • Climate 'exogenous' shock defined as 2015 Paris agreement as major 'climate policy change' • DD Model F(Carbon Intensity) • Partial, comparative static model
SCOPE/DATA	• Corporate debt & residential mortgages • Dutch banking system – exposure data for 2017 • 2,346 Listed firms from EU15 index to calibrate Merton DD model • Carbon 'vulnerability' ('intensity') assessed using Eurostat SBS data on emissions	• 458 listed firms with bonds • 2007-2017 data • Considered Scope 1 direct emissions only sourced from Asset4
IMPACTS	• Bank asset value declines up to 63% worst case • EU200 shock yields up to 63% decline in Dutch Banking CET capital	• Higher emissions footprint/intensity reduces firm default distance set par

8: Publications: Credit Risk Modelling, PIT/TTC Ratings, Z-Risk Engine

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

8: Publications: Credit Risk Modelling, PIT/TTC Ratings, Z-Risk Engine cont

- 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
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- 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.*