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Quantifying the Financial Impacts of Climate Change

A Unified Approach to Physical and Transition Risk

Robert F. Brammer, Ph.D., Matthew Lightwood, Ph.D., Clifford Rossi, Ph.D.

Executive Summary

1. The growing threats of extreme weather and climate tipping points create risks to financial markets in the next five to ten years that current climate scenarios do not capture.[1]

2. We introduce a class of stochastic sector-specific damage functions to capture the probabilities of significant events, notably extreme weather and climate tipping points.[2] Using these models will show material climate-related risks for insurance and pension fund asset allocations in the next five to ten years.

3. The stochastic character of the damage functions enables the calculations of climate stresses at various percentile levels rather than just a single deterministic path as is currently the case in most regulatory stress tests.

4. EIOPA recently pointed out the need to consider the interaction between physical and transition risks.[3] We introduce feedback between physical and transition risk, which captures our belief that carbon abatement on a significant scale will not happen before more significant physical damage occurs. For instance, we recognize that there is considerable current transition energy investment in the US, with a 2021 total for US transition energy investment of over $110B (mainly in renewable energy and electric vehicles).[4] However, the value of assets potentially stranded by climate-related legislation and regulation could be as high as $14T.[5]

5. We analyze the impact of the defined scenarios on various asset classes using Conning's Climate Risk Analyzer™. For example, we show that including a scenario that incorporates possible climate tipping points can reduce the expected cumulative return over the next ten years for a portfolio of mortgage-backed securities from 9.4% to an expected loss of 1%, with a 5% chance of a loss of 14.8%.

6. Stochastic methods which generate a probability distribution of climate risk outcomes can provide a more robust way of understanding the "tail" of a climate risk distribution than can single-scenario analyses. Recent research has shown a growing threat of such abrupt and irreversible climate changes by 2030.[6, 7]

Introduction

Since the Global Financial Crisis (GFC), financial stress tests and scenario analysis have become standard regulatory-required practices. These analyses, including data, models, and relatively short time horizons, have taken years to develop and refine. The growing risks of climate action failure and extreme weather are causing increasing concerns about potential impacts on the global financial system (e.g., the World Economic Forum report in January).[8] Accordingly, there are initial actions to pilot climate stress testing into insurance and pensions regulatory frameworks in many countries.[9]

The push toward including climate stress testing within the ORSA poses significant challenges to both regulators and insurance and pension undertakings. These challenges are partly due to the reliance on climate models and associated integrated assessment models (IAMs), where empirical linkages to financial instruments, products, and services are not well-established. The relative mismatch between the long time horizon of climate models and the shorter strategic planning horizons required by the ORSA is also a significant additional complication.

1 We define a tipping point as a critical threshold beyond which a system reorganizes, often abruptly and irreversibly.
2 Lontzek, T., "Stochastic integrated assessment of climate tipping points indicates the need for strict climate policy," Nature Climate Change, 23 March 2015.
3 EIOPA – Methodological Principles of Insurance Stress Testing – Climate Change Component, 27th January 2022.
4 BloombergNEF, "Energy Transition Investment Trends 2022, January 2022.
5 Mercure, J., et al., "Reframing incentives for climate policy action," Nature Energy, Vol.6, December 2021.
6 Lenton, T., et al., "Climate tipping points — too risky to bet against," Nature, 9 April 2020.
7 Dietz, S., "Economic impacts of tipping points in the climate system," Proceedings of the National Academy of Sciences of the United States of America, 13 November 2021.
8 World Economic Forum, "The Global Risks Report 2022," January 2022 lists climate action failure and extreme weather as the top two "most severe risks on a global scale over the next ten years."
9 For example, the Bank of England and the European Central Bank conduct pilot projects.

In this paper we introduce some of the major conceptual ideas within current climate economics models used for the calculation of the financial costs of physical climate risk and the transition to a low-carbon economy. We then propose a methodology that extends the current literature to consider the uncertainty in current deterministic forecasts of climate-related financial damages, as well as the potential for higher-than-expected realized losses in the short term due to tipping-point-type events. Rather than treating physical and transition risk as independent, our model also introduces feedback between physical damages and government action on carbon abatement, which we consider more realistic given the slow progress of climate politics to date. Finally, we use simulations from the GEMS® Economic Scenario Generator ("GEMS") to apply the climate scenarios to various types of market and credit risk exposures using the Conning Climate Risk Analyzer™ ("Climate Risk Analyzer"). We present a range of metrics and comparative distributions for the market value of several different asset classes under a best-estimate scenario and a scenario conditioned on a particular climate change scenario

Using this model, insurance and pension firms could augment their current stress testing frameworks, implement climate scenarios broadly aligned with the current thinking of European and North American regulatory requirements on the ORSA, and partially satisfy many other reporting standards, such as those from the Taskforce for Climate Related Financial Disclosures (TCFD) and the Principles for Responsible Investing (PRI).

Climate Impact Modeling

Physical Risk

Physical risks arise from the physical effects of climate change and are perhaps more closely related to how we naturally perceive climate risk. These include acute physical risks, which might arise from weather-related events such as storms, floods, fires, or heatwaves and which may damage physical property and disrupt the operations of companies that we invest in. More subtle are chronic physical risks which manifest themselves over longer time horizons, such as rising sea levels, changes in temperature, and reduced water availability. In more detailed analyses, tertiary physical effects of climate change on biodiversity, soil quality, migration of people, higher incidence of conflicts, and other sources might also be considered.

A common approach to modeling physical climate-related risks is to employ a financial damage function relating global temperature changes to impact on output, consumption, or other economic variables. The following form of the financial damage function for physical risks is often used as the starting point of these assessments.[10]

$$\Delta(t) = a_1 \Delta T_t + a_2 \Delta T_t^2$$

10 We have chosen to use the quadratic form as a basis of our model because it is the most commonly used and referenced function in the definition of financial stresses at this time. New models are becoming more focused on severe and worst-case outcomes, moving away from the assumption that temperatures can be contained within the 2- to 2.5-degree range. More research based on these models will be performed in the future.

Model	a_1	a_2
Nordhaus	0	-0.00267
Howard and Sterner	0	-0.007438
Kalkhuhl and Wenz	-0.0373	-0.0009

Table 1 Proposed parameterizations of the quadratic damage function, from Nordhaus, Howard and Sterner, and Kalkhuhl and Wenz.[11, 12, 13]

Where *Δ(t)* is the expected financial damage from climate-related physical effects at a time, *t*, due to changes in temperature relative to pre-industrial levels ΔT_t. **Table 1** shows some leading parameterizations for α_1 and α_2,

Once an assessment of physical damage—typically expressed in terms of a fraction of GDP—is made it can be cascaded down to asset class or individual equity or fixed income holdings using some assumptions about the exposure of the asset to the physical damage.

Transition Risk

Transition risks may be described as risks that arise from the transition to a low-carbon economy. These might include risks arising from policy changes such as energy efficiency regulations or carbon pricing mechanisms, which in turn increase the cost and relative attractiveness of fossil fuels. Further, they may more broadly include risks arising from disruptive technologies, which might rapidly replace a technology that is more damaging to the climate. Changes in consumer habits and reputational elements may also be considered to fall under the "transition risk" definition.

The current methods used for quantifying the financial impacts of transition risk usually begin with an assumption about the future path of the cost of carbon. This usually involves estimating how much carbon taxes might need to increase over the next thirty or fifty years to maintain global warming below some threshold, say 1.5° C. In this type of scenario definition, the analyst implicitly assumes that governments will act in some rational way to mitigate the longer-term negative effects of climate change (i.e., physical risk).

Given a cost-of-carbon scenario as input, a marginal abatement curve can be used to compute the cost of carbon abatement at a particular level as a fraction of GDP. The marginal abatement curve relates the carbon price to the emissions control rate. The emissions control rate is defined as the proportion of total emissions that a rational player would abate at the given level of the carbon price. An example of a marginal abatement curve is shown in **Figure 1** (following page).

11 Nordhaus, W. D., Sztorc, P., DICE 2013R: Introduction and User's Manual, p.97.
12 Howard, P. H., and Sterner, T., "Few and not so far between: a meta-analysis of climate damage estimates." Environmental and Resource Economics, 68(1), 197-225. (2017).
13 Kalkuhl, M., & Wenz, L., "The Impact of Climate Conditions on Economic Production. Evidence from a Global Panel of Regions.," Journal of Environmental Economics and Management, 2020, vol. 103, issue C.

The marginal abatement curve assumes an equilibrium model in which a rational agent would have an incentive to abate a certain proportion of carbon emissions (x-axis) for a given carbon price level (y-axis). The form of the curve usually follows a power law assumption (typically quadratic) which is consistent with the idea that reducing the first x% of carbon is cheaper than eliminating the last y%.

Marginal abatement curves are a useful construct because they relate the carbon price with the cost of abatement. For a given carbon price, c(t), input from a future transition risk scenario, the abatement cost per ton of carbon emissions can be calculated as the integral under the curve to *c(t)*, as shown in Figure 1, with the remaining area up to an ECR of 1 (100% of emissions) representing the tax per ton of carbon emissions which must be paid. Given then a projection of total unabated emissions, the cost of abatement as a fraction of GDP can be estimated.

It should be noted that there are many sources of marginal abatement curves,[14, 15] as well as debate around the current cost of carbon. This is a possible source of uncertainty in the modeling of these financial risks which is worth considering.

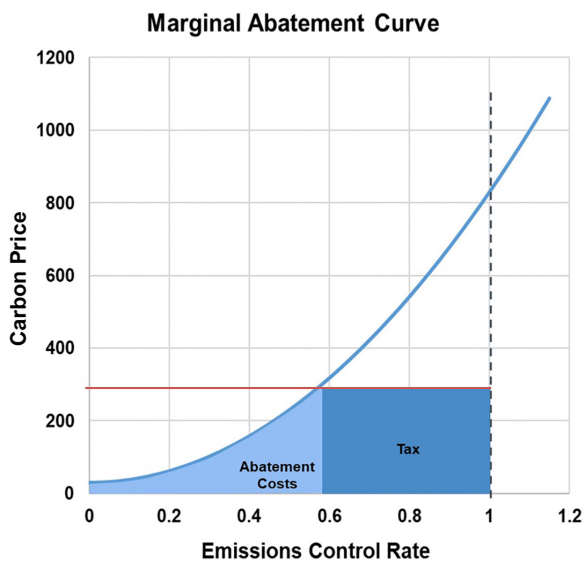

Figure 1 Example marginal abatement curve showing the calculated abatement cost and tax at the given carbon price level (red line). ©2022 Conning, Inc.

Climate Modeling Limitations

The basis of many scenarios of financial climate risks are models of future global warming and the impact that this will have on world weather and geophysical systems. It is perhaps then worthwhile to briefly consider the limitations of these models.

Models used today for estimating climate scenarios represent simplified forms of the physics of a complex Earth system well into the future. While the models have had some successes, the scientific community has recognized many limitations.[16] There is work now to develop a new generation of models to overcome many shortcomings.[17] Among these significant limitations is the fact that their output is of limited near-term use by financial institutions.

Although a new generation of climate models and IAMs will be a significant advance, we need not wait until this new generation is available to make substantial progress in analyzing the risks to the financial system. A collaboration of the scientific and financial communities is already at work to better understand the capabilities and limitations of these models and to develop scenarios to guide a pragmatic approach to climate risk policy for regulated institutions. A key question for risk analysts should be how to understand these risks in a way that is relevant on a strategic planning horizon. This in turn will motivate boards and key decision makers to follow the old adage in medicine, "First, do no harm." However, "Second, do something quickly."

A pivotal study released by the United Nations' Intergovernmental Panel on Climate Change (IPCC) in 2018 noted that CO_2 emissions would need to fall nearly 50% by 2030 to prevent global temperatures from rising more than 1.5 degrees Celsius, a goal of the Paris climate agreement.[18] The IPCC 6th Assessment Review in 2021 updated this study and the Paris climate agreement to spur calls of urgency among climate risk advocates and others.[19] The models upon which such urgent demands for public policy response are based contain significant model risk. Model risk is associated with errors in data, methods, or assumptions used to generate output from analytical models used for decision-making. Effective risk management and public policy decision-making must have a foundation of a sound understanding of the current state and limitations of climate and the IAMs.

As we have mentioned previously, the long-term nature of most explicitly defined climate stress tests to date makes them difficult to implement in practice for many financial institutions. Moreover, empirical linkages between typical financial and risk performance outcomes and climate-related outputs are not well-established. The existing risk models are incompatible with the scenario time horizon, rendering a deterministic single-scenario analysis of limited value for risk assessment. **For these reasons and others, conducting stress and scenario analysis over a more extended period using a deterministic approach, based on only an ex-**

14 Cline, W. R., 2011 op. cit. Carbon Abatement Costs and Climate Change Finance.
15 McKinsey Sustainability, "Greenhouse gas abatement cost curves," mckinsey.com.
16 Palmer, T. and Stevens, B., "The scientific challenge of understanding and estimating climate change," Proceedings of the National Academy of Sciences, V 116, No. 49, 3 December 2019.
17 Bauer, P., et al., "The digital revolution of Earth-system science," Nature Computational Science, v 111, February 2021.
18 IPCC, 2018: Summary for Policymakers. In: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. World Meteorological Organization, Geneva, Switzerland, 32 pp.
19 IPCC, 2021, "Sixth Assessment Report," https://www.ipcc.ch/assessment-report/ar6/

pected or most likely scenario, is unreliable in understanding and managing a firm's risk profile today.

Other commonly used sources of climate scenarios are those developed by entities such as the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), which rely on projections extending decades into the future. The NGFS's six climate scenarios characterizing the effects of transition and physical risks to the financial system from changes in public policy, temperature, and emissions extend to the year 2100.[20] These climate and socioeconomic models operate on a global scale with a complexity and long-term horizon incompatible with the level of granularity required and relatively shorter-term focus of most portfolio risk analyses. These scenarios are also subject to much model risk, as is acknowledged by the NGFS in their discussion of climate scenario development: *Modelling the GDP impacts from transition risk and physical risk is subject to significant uncertainty.*[21]

A recent evaluation of the world's leading climate models shows that the predictions from the various models are not converging. The World Climate Research Program's "Coupled Model Intercomparison Project" compares model projections from the world's leading climate models.[22] In its 6th phase (CMIP6), approximately 100 models from organizations worldwide participated. Scientists use the critical metric "Equilibrium Climate Sensitivity" (ECS) in comparing models. The ECS is the model output in response to a shock doubling the input of atmospheric CO_2 concentrations. The climate modeling community uses this metric as a significant indicator of the severity of future warming. If the models were converging to consistent results, the differences among ECS values produced by the CMIP models would shrink. Unfortunately, the range of ECS values among the CMIP6 models is greater by 45% than the range calculated by the earlier CMIP5 models.[23, 24]

In his seminal article, "The Use and Misuse of Models for Climate Policy," Pindyk levies a damning indictment of the current generation of IAMs, including the arbitrary parameterization and assignment of model input functional forms, difficulty in understanding climate sensitivity impacts to the models, a lack of data relating to damage functions, and poor characterization of tail risk associated with climate outcomes.[25]

Climate Economics Modeling Limitations

We differentiate the climate models described in the last section, which are intended to model the effect of changes in greenhouse gases on Earth's geophysical properties (e.g., sea level or temperature), from climate economics models which try to describe the impact of climate change on financial or macro-economic variables. The current modeling approaches used to quantify physical and transition risk which were described in prior sections 3 have several significant limitations which are independent of pure climate model limitations. These limitations include:

1. There is no treatment of the uncertainty of damages to GDP through increases in the Social Cost of Carbon (SCC), Δ. These uncertainties are likely to be significant, as evidenced by the variance in the model parameterizations shown in Table 1 (page 2). For example, the coefficient a_2 in the Howard and Sterner model is three times larger than the coefficient in the Nordhaus model and more than seven times larger than this coefficient in the Kalkhuhl and Wenz model.

2. There is no way of incorporating the effects of medium- to low-probability but high-impact events caused by tipping points. The above models do not include climate tipping points, and the above references do not discuss this topic. Currently to our knowledge, regulatory climate stress tests have also failed to address tipping points despite the potential for high impacts, albeit with low probability, in the short to medium term.

3. Physical and transition risk scenarios are treated independently from one another as shown in **Figure 2**. To define a scenario, the user must provide two sets of inputs, one for the future temperature change and one for the future cost

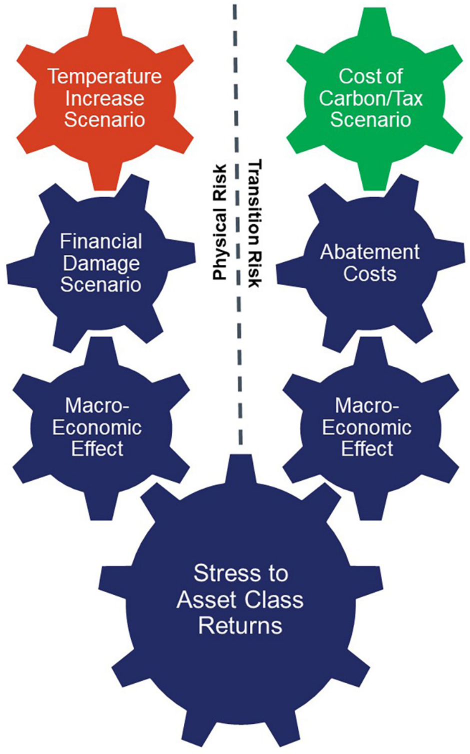

Figure 2 Representation of the process for defining physical and transition risk scenarios in current risk management frameworks. ©2022 Conning, Inc.

20 Network for Greening the Financial System, NGFS Climate Scenarios for central banks and supervisors, June 2021.
21 Ibid.
22 Wikipedia, The Free Encyclopedia, "Coupled Model Intercomparison Project," (accessed May 3, 2022), https://en.wikipedia.org/wiki/Coupled_Model_Intercomparison_Project
23 CarbonBrief, "CMIP6: the next generation of climate models explained," carbonbrief.org, 2 December 2019.
24 Zelinka, M., "Causes of Higher Climate Sensitivity in CMIP6 Models," Geophysical Research Letters, 3 January 2020.
25 Pindyk, R.S., The Use and Misuse of Models for Climate Policy, Review of Environmental Economics and Policy, 11, 1, Winter 2017, 100-114.

of carbon. More importantly, there is no feedback between the two when arguably transition risk should be led by physical risk (i.e., physical damages mount, causing political and financial incentives to increase the abatement of carbon-intensive practices and mitigate future damages).

The limitations of these models, as well as the climate models and IAMs discussed in the last section, reduce the utility of single-path deterministic climate scenarios for financial market climate risk analysis and strongly motivate the need for a probabilistic approach. Augmenting these scenarios with a distribution of climate risk outcomes based on current leading research on extreme weather and climate tipping points is likely to significantly improve the utility of results.

In the next section we propose an extended climate economics model which provides a viable methodology to reduce the problem of defining scenarios for financial market asset allocations to a functional form with interpretable parameters that can be set by analyzing more complex models of climate change impacts. The model's output is such that insurance and pension funds could implement and report on the short- and medium-term effects of defined scenarios more quickly and easily.

An Integrated Approach to Defining Physical and Transition Risk Scenarios

In their 2022 paper, *Methodological Principles of Insurance Stress Testing—Climate Change Component*, EIOPA note that, *"Physical and transition risks are interlinked and affect financial firms in distinct ways. The initial approaches taken by supervisors to better understand the impact of climate change tend to treat the two risks separately. The same approach is taken by the academia where much of the existing production focuses on one element or the other in insulation. Although approaching the two risks separately might help from a theoretical and operational perspective, by simplifying the analysis and enhancing transparency, it neglects to understand the interplay between the two risks. The complex dynamic between physical and transition risks can generate both mitigating and mutually reinforcing effects."*[26] This further reinforces the need and regulatory demand for an integrated model of physical and transition risks of the type that we have developed.

To address this as well as some of the other limitations already discussed, we propose a stochastic extension that gives regulators and risk analysts much broader information on the range of financial damages that might occur in a given climate scenario. Further, we suggest a simplified methodology to cascade these damages to investible asset classes and apply them to existing financial market risk frameworks. The model unifies the approaches to modeling physical and transition risks discussed earlier, incorporates tipping points, and allows for the range and probabilities of possible outcomes to be estimated.

26 EIOPA – Methodological Principles of Insurance Stress Testing – Climate Change Component, 27th January 2022

We start by proposing a unified model of physical and transition financial damages of the form:

$$\Delta(t) = \alpha_1 \Delta T_t + \alpha_2(t) \Delta T_t^2 + \phi_{Trans}(t)$$

Note that this process is similar to the standard physical damage function shown earlier, but the static parameter a_2 is replaced by a stochastic process, $\alpha_2(t)$ which scales the quadratic term in ΔT_t. The term, $\varphi_{Trans}(t)$, describes the feedback between physical damage and transition risk, and it will be discussed in more detail later.

Several forms could be used to describe the random element $\alpha_2(t)$; however, we assume that the uncertainty around the central assumption of the parameter is a white-noise term with a jump and is given by:

$$\alpha_2(t) = a_2 + \sigma dW(t) + (e^{\gamma} - 1) dN(t)$$

Where;

- a_2 is a fixed parameter from one of the models shown in Table 1,
- σ is a parameter controlling the variance of the process,
- $dW(t)$ is a Wiener process,
- $N(t)$ is a Poisson counter with intensity $\lambda.\Delta T^{v}$, and
- $\gamma = N(m_\gamma, \sigma^2_\gamma)$ is a Gaussian random variable but could equally be a constant.

The variance parameter, σ, represents the uncertainty around the base assumption, a_2. The jump process $dN(t)$ incorporates low-probability high-impact events into the simulation. This process enables us to include the possibility of tipping-point events that might lead to unanticipated severe losses at any temperature level. This simplified structure allows us to incorporate the conclusions of more complex models, which consider the impacts of tipping points from studying the geophysical processes involved.

Note that the intensity of the jump process increases with ΔT^{v}, such that the probability of tipping points increases with temperature, and the parameter v captures the non-linearity in the likelihood of such events. Due to the stochastic process driving $\alpha_2(t)$, the model can produce positive outcomes for a given temperature change scenario. The output will always be skewed negatively by parameter a_2, which is negative for all parameterizations of the damage function, and the jump process, which has a negative mean. Purely economic and financial market opportunities may result from innovation, low-tax regimes for green technology, and the positive economic effects of rebuilding infrastructure and physical assets damaged by climate-related events. However, the model's primary objective is to understand worst-case outcomes from a market-risk perspective. A non-zero (i.e., likely minimal) probability of positive results should not mitigate or reduce the probable substantial negative impacts of global temperature changes on the world's economy.

We now describe the model of the transition term Φ_{Trans}(t). Consistent with current practice, we start with the assumption that increases in the cost of carbon will be the primary driver of carbon reduction. As we have seen, most approaches to scenario definition for transition risk assume some path for the cost of carbon and then compute the abatement costs based on this path. Our process differs because we believe physical damage will be the primary driver of transition risks. The propagation mechanism for transition risk in this framework could be from higher physical damage causing enough political pressure to force the implementation of carbon taxes, tariffs, or other methods for raising the cost of carbon. Increasing physical damages may also lead investors to pressure companies to buy more carbon credits, increasing the prices and costs for some companies or sectors.

As evidenced by the last thirty years of experience, there is likely to be little political incentive to drive the cost of carbon higher until physical damage exceeds some threshold, τ. There are many examples that reinforce this assertion. A particularly prescient one at the time of writing is the severe floods experienced in Germany in 2021. In large part, this event contributed to the Green Party increasing its number of parliamentary seats in the Bundestag from 67 to 118 and took the party into the ruling coalition. Another example is US wildfires, where, as we will discuss in some more detail later, spending on wildfire mitigation lagged wildfire damage. However unfortunate the conclusion, it would seem logical that given a typical electoral cycle of 3 to 5 years, governments are unlikely to significantly increase the cost of energy, transport, food and other goods that rely on carbon intensive practices until the incentives are obvious and compelling to the voting public that they rely on. The Ukraine crisis of 2022 has shown how intolerant the public is to rises in energy costs, which to date have been moderate when compared to some of the scenarios for the cost-of-carbon increases that would be required to maintain global warming within 1.5°C relative to pre-industrial levels.

In our model, rather than assuming governments will collectively act in some way which would require the user to define how the cost of carbon will evolve in the future, the cost-of-carbon is determined stochastically based on what the current simulated level of physical damage is. Under this framework, the cost of carbon (per ton) C(t) is given by;

$$C(t) = \begin{cases} C(t-1), & \alpha_1 \Delta T_t + \alpha_2(t)\Delta T_t^2 > \tau \\ C(0) + \Delta C(\Delta_{phys}(t), t), & \alpha_1 \Delta T_t + \alpha_2(t)\Delta T_t^2 \leq \tau \end{cases}$$

The threshold τ is negative and physically represents human tolerance to climate-related financial damage. *C(0)* is the current cost of carbon, and $\Delta C(\Delta_{phys}(t),t)$ is the change in the cost of carbon at time t, which is a function of the physical part of the damage function $\Delta_{phys}(t) = \alpha_1 \Delta T_t + \alpha_2(t)\Delta T_t^2$. Hence, there is feedback between the stochastic physical damages, $\Delta_{phys}(t)$, and the change in the cost of carbon, $\Delta C(\Delta_{phys}(t),t)$.

We assume an equilibrium relationship between the costs of physical damages above the threshold τ and changes in the cost of carbon. The increase in the cost of carbon, $\Delta C(t)$ $(=\Delta C(\Delta_{phys}(t),t))$, is derived from:

Total Abatement Investment $= |c.(\Delta^{phys}(t) - \tau)|.GDP(t) = \Delta C(t).V_{em}(t)$

Where *GDP(t)* is the global (but could be country or regional) GDP (in \$), and $V_{em}(t)$ is the projected level of emissions at time *t* if no abatement were to occur. The parameter *c* is the proportion of physical damage above the threshold invested by governments in abatement. This structure allows for feedback between physical damages and transition costs by calculating the value of $\Delta C(t)$ from the above at each point in the simulation. We further assume that $\Delta C(t)$ can only increase or remain at the current level in the final implementation of the model (i.e., policy decisions are irreversible).

Given that we have now calculated the equivalent cost of carbon on each stochastic path of the unified damage function, it is possible using a marginal abatement curve to quantify the transition term $\Phi_{Trans}(t)$ as a fraction of GDP:

$$\phi_{Trans}(t) = \left[\int_0^{\mu(C(t))} M(\mu).\,d\mu\right].V_{em}(t)/GDP(t)$$

Where $\mu(C(t))$ is the equilibrium value of the emission control rate, μ, corresponding to the cost of carbon *C(t)*, and $M(\mu)$ is the marginal abatement curve.

Note that the marginal abatement curve could be assumed to follow a parametric and integrable form or could be solved numerically. In the studies that follow we will assume a quadratic form that is similar to the structure of the abatement curve that Nordhaus uses in his DICE model.[27] Several approaches exist to construct marginal abatement curves, including our top-down approach and various bottom-up approaches.[28] Incorporating these alternative methodologies into our overall framework is straightforward because our model only requires that the marginal abatement curve is either analytically or numerically integrable.

A final level of granularity is that, like Nordhaus, we also assume that abatement costs will fall as more and cheaper technological options become available. So, while our model assumes the cost of carbon will increase over time (or remain stable), the proportion of carbon abated for a given carbon price will also increase. In our model we follow a commonly used assumption of a 2.5% reduction in abatement cost every five years.

Considering the initial formulation of our integrated stochastic damage function again, we have described all of the required elements needed to compute the function.

$$\Delta(t) = \alpha_1 \Delta T_t + \alpha_2(t)\Delta T_t^2 + \phi_{Trans}(t)$$

27 DICE 2013R: Introduction and User's Manual, 2013. P91. Nordhaus uses k = bμβ where k is the abatement cost as a fraction of GDP and assumed a near cubic relationship with β=2.8. So the assumed marginal abatement curve is close to quadratic (because the integral of μ2 is 1/3.μ3).

28 Cline, W. R., 2011 op. cit. Carbon Abatement Costs and Climate Change Finance.

The inputs to the model are:

1. A temperature increase scenario to derive $\Delta T t$.
2. A projection of $GDP(t)$ into the future.
3. A projection of $V_{em}(t)$ into the future.

There are also various model parameters that the user can adjust in addition to these inputs. We discuss suggested values for the model parameters in the next section.

In comparison to Figure 2, **Figure 3** shows schematically the order of events in the model described above. We see that the proposed model has taken the previously separate domains of physical and transition risk and unified them into a framework that allows us to explore the range of damage function outcomes that might be experienced under a given temperature increase scenario.

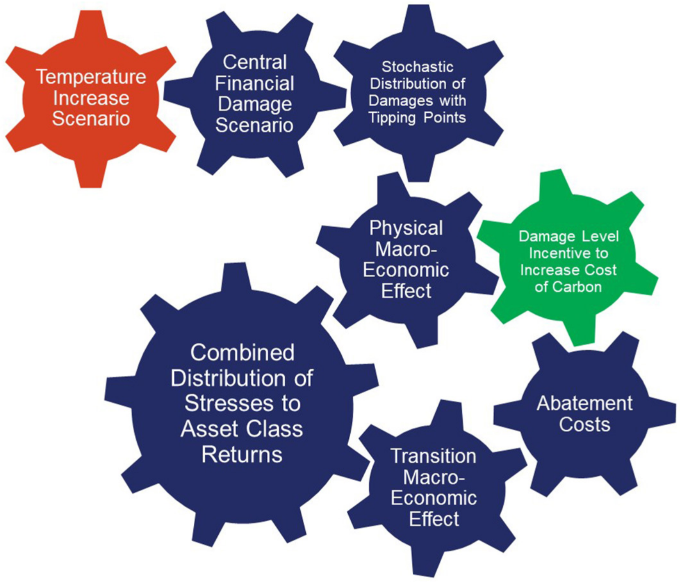

Figure 3 Representation of the process for defining physical and transition risk scenarios under a unified stochastic damage function. ©2022 Conning, Inc.

Model Setup and Parameter Values

The nature of forward-looking scenario analysis of unprecedented events means an absence of historical data available to set the values of model parameters. Accordingly, we provide for the use of expert analysis and judgment in determining model parameters.

As part of defining scenarios, we have analyzed the current state of climate damages and government responses and have used existing research to inform the setting of model parameters. We discuss below the parameter values used and the reasoning behind the choice for the studies that follow.

σ (= 0.0066) – We use the Howard and Sterner damage function as our central assumption and determine parameters such that one standard deviation of $\alpha_2(t)$ corresponds to the distance between a_2 for this model and the Kalkuhl and Wenz model (-0.007438 – -0.0009). This choice is the most severe of the existing damage function models that we use as a starting point.

(λ, v) (= 0.02, 1.632) – The jump intensity is set such that the probability of a jump at the 1°C level of warming is 1:50 years, which increases as ΔT increases ($\lambda.\Delta T^v$ is the intensity used, and the probability of a jump at a given degree of warming is $1/\lambda.\Delta T^v$). While it is difficult to estimate the likelihood of a climate tipping point, the IPCC judges there to be a significant probability even at today's level of warming, and this would become "high" for temperature rises >2° and "likely" at >4°.[29] Consequently, we choose the parameter v such that the probability of a jump is 1:5 years at the 4°C level of warming and 1:16 years at the 2°C level.

$(m\gamma, \sigma 2\gamma)$ (= -0.0095, 0.0093) – We choose the jump size mean and standard deviation to be consistent with the conclusions by Dietz et al.[30] We do this in order to have a geophysical basis of tipping points for our simulations and to capture the possible effects of a range of tipping point threats. We fix the mean jump size parameter at the level implied by 2.5-degree warming in this reference study. The jump variance value spans the range of additional damage due to tipping points shown in that paper. This approach is one of the main developments within our model—namely, incorporating the conclusions derived from a complex model of geophysical processes involved in tipping points within a simple Poisson jump process model.

τ (= -0.04) – We chose the transition threshold, τ, which governs the level of physical loss (as a proportion of nominal GDP) at which governments will start to act on carbon prices and trigger the onset of significant transition risk as -4% of GDP. This choice is, to some extent, an expert judgment, depending as it does on the future demands and expectations of the voting public. In setting the parameter, we have considered the costs of disasters since 1980,[31] as shown in Figure 4.

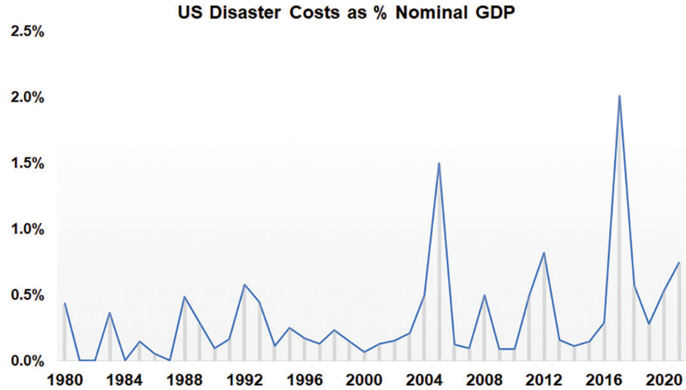

Figure 4 Cost of natural disasters in the US as a fraction of GDP (Prepared by Conning, Inc. Sources: National Oceanic and Atmospheric Administration, National Centers for Environmental Information. (2022): U.S. Billion-Dollar Weather and Climate Disasters, Retrieved April 12, 2022, from https://www.ncei.noaa.gov/access/ billions/time-series/US and ©2022 Bloomberg L.P.).[32]

29 Lenton,T., et al, op. cit.
30 Dietz, S., et al., op. cit.
31 NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2022). https://www.ncei.noaa.gov/access/monitoring/billions/, DOI: 10.25921/stkw-7w73
32 Ibid.

This chart shows that we have already experienced natural climate-linked disasters with costs above 2% of GDP. We therefore conclude that it would require significantly higher impacts to drive policy change in the area of carbon price increases, and thus set the threshold at 2% above the worst year to date (2017).

c (= 0.623) – The parameter c governs the proportion of the cost beyond the threshold τ that we expect government and industry will spend on abatement. We chose this value by considering wildfire costs in the US and government spending on wildfire mitigation and management between 2011 and 2020.[33] We chose wildfires for two reasons. First, they are an immediate and current example of political pressure forcing governments to commit federal dollars to climate-related disasters. Second, data sets are available on both costs and budget allocations, which allows for inferring the model parameter. Using this data, we put parameter c at the average ratio of government spending and wildfire disaster costs between 2011 and 2020. It is also interesting to note that the 2021 flood damage in Germany is currently about EUR 40bn with federal support packages of EUR 30bn. This data further supports the notion that c should be less than 1 and in the range of 50%–75%.

Choice of Climate Scenarios

Other than the model parameters, the only input to the model is a scenario for how temperatures might evolve over the time horizon of the analysis. To make the analysis as broad-ranging as possible, we have defined scenarios for the next thirty years, encompassing the medium-term horizons most relevant to insurance firms within the context of the ORSA. There are many potential sources of such climate change scenarios, including the Representative Concentration Pathways (RCPs) from the Intergovernmental Panel on Climate Change (IPCC),[34] the Network for Greening the Financial System (NGFS),[35] and the Shared Socioeconomic Pathways.[36]

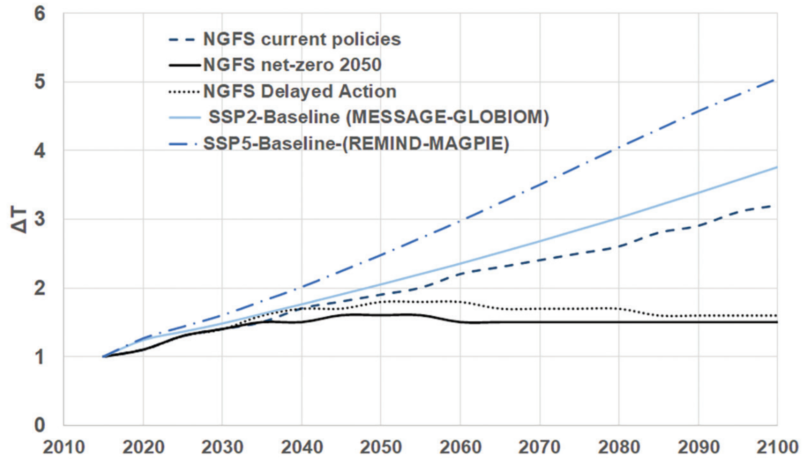

Figure 5 Commonly used climate change scenarios equivalent to the NGFS and Shared Socioeconomic Pathways shown. (Prepared by Conning, Inc. Source: IAMC 1.5°C Scenario Explorer hosted by IIASA (release 2.0)).

Figure 5 shows some of the pathways from these sources. For the analysis in this document, we will illustrate our process with the SSP-5 baseline scenario. The SSP scenarios have the advantage of a widely used scenario narrative with data available for the inputs that our model requires, in particular temperature change projections. We choose to focus on SSP-5 because it is the most severe of the scenarios defined; however, any of the SSP scenarios could be incorporated with ease. The underlying narrative for SSP5 is a future in which societies continue to exploit fossil-fuel resources and pursue energy-intensive lifestyles globally, leading to continuing growth of the economy. Investments are made in technology, health, and education instead of alternative energy sources. In this scenario, the global population peaks in the 21st century and then begins to decline.

Stresses Derived for Specific Asset Classes

By using the temperature scenario under SSP-5, we can now use the model to simulate the stochastic damage function *Δ(t)*. The result of this simulation is a distribution of possible financial damage for the next thirty years, as shown in **Figure 6**.

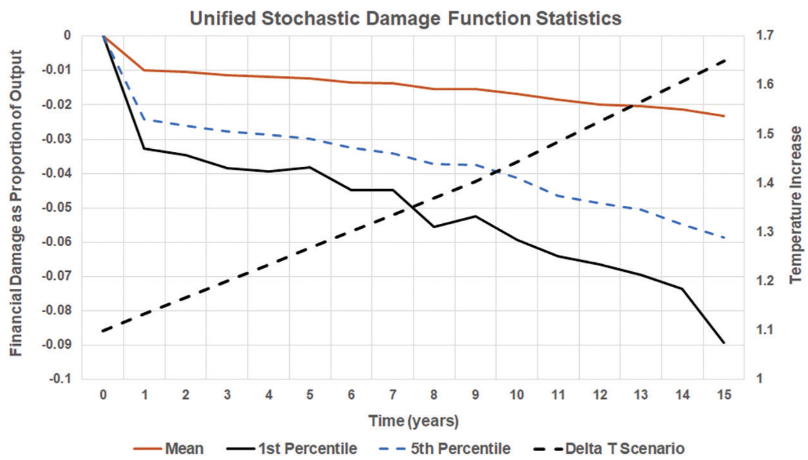

Figure 6 SSP5 temperature change scenario (black hatched, right axis), and the projected mean, 5th and 1st percentile of the distribution of damages as a proportion of GDP from the integrated physical and transition risks model. (Prepared by Conning, Inc. Source: IAMC 1.5°C Scenario Explorer hosted by IIASA (release 2.0)).

33 Congressional Research Service, Federal Wildfire Management: Ten-Year Funding Trends and Issues (FY2011-FY2020), 28 October 2020.

34 IPCC Data Distribution Centre, https://www.ipcc-data.org/guidelines/pages/glossary/glossary_r.html

35 Daniel Huppmann, Elmar Kriegler, Volker Krey, Keywan Riahi, Joeri Rogelj, Steven K. Rose, John Weyant, Nico Bauer, Christoph Bertram, Valentina Bosetti, Katherine Calvin, Jonathan Doelman, Laurent Drouet, Johannes Emmerling, Stefan Frank, Shinichiro Fujimori, David Gernaat, Arnulf Grubler, Celine Guivarch, Martin Haigh, Christian Holz, Gokul Iyer, Etsushi Kato, Kimon Keramidas, Alban Kitous, Florian Leblanc, Jing-Yu Liu, Konstantin Löffler, Gunnar Luderer, Adriana Marcucci, David McCollum, Silvana Mima, Alexander Popp, Ronald D. Sands, Fuminori Sano, Jessica Strefler, Junichi Tsutsui, Detlef Van Vuuren, Zoi Vrontisi, Marshall Wise, and Runsen Zhang. IAMC 1.5°C Scenario Explorer release 2.0 and Data hosted by IIASA. Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis, 2018. doi: 10.22022/SR15/08-2018.15429 | url: data.ene.iiasa.ac.at/iamc-1.5c-explorer

36 Riahi, K. et al., "The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview," Global Environmental Change, Volume 42, January 2017, Pages 153-168.

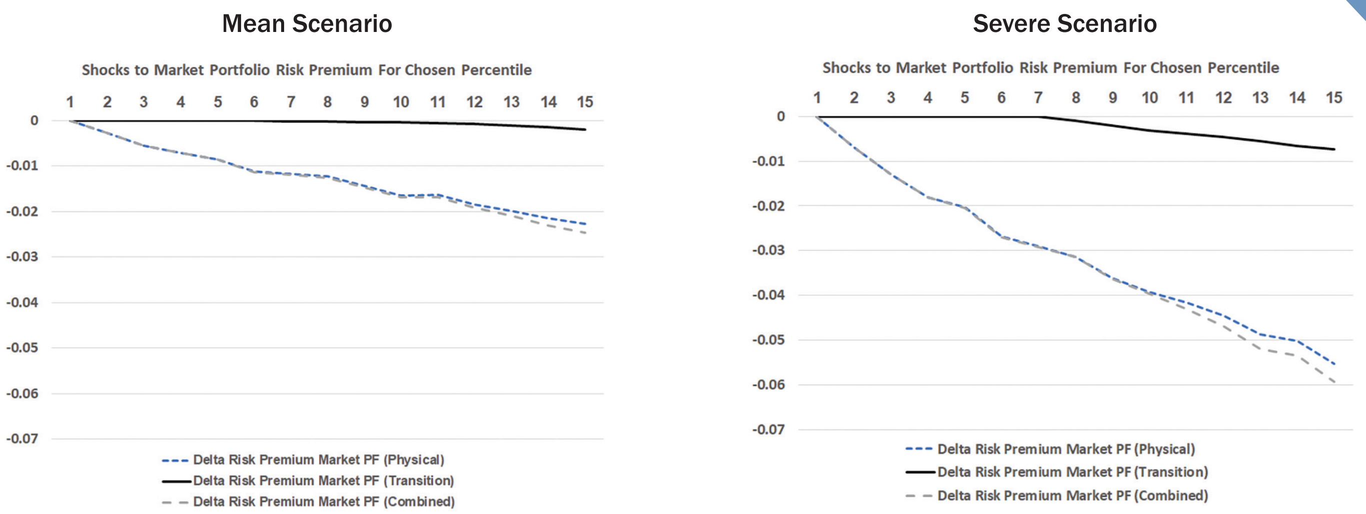

Figure 7 Estimated reduction in market portfolio risk premium over the next 15 years from physical (blue hatched), transition (Black solid), and combined (grey hatched) climate risks under the SSP5 scenario. The left-hand graph shows the mean projected damage function from the integrated physical and transition risks model. The right-hand graph shows the lower 5th percentile of the projected distribution of damages from the model. (©2022 Conning, Inc.).

Figure 6 shows the mean, the 1st, and the 5th percentile financial damage as a fraction of global GDP. We will use only the mean and the 5th percentile as the basis of our stress test definition, and from now on we will refer to these as the "mean scenario" and "severe scenario." The use of the 5th percentile is somewhat analogous to the VAR calculations widely used in risk management.

There is no generally agreed standard or entirely robust methodology for cascading impacts on the social cost of carbon as a fraction of GDP down to equivalent shocks in investable asset classes (e.g., equities or corporate bonds). Nevertheless, to make scenario analysis based on our model practicable, it is essential to link damage functions on GDP with damage function in the financial markets. We use an autoregressive model of GDP and model a market portfolio in GEMS in order to cascade the mean and severe scenarios from Δ(t) into shocks on the market portfolio risk premium. We construct the market portfolio based on weightings from the academic literature.[37] For SSP-5, we illustrate in **Figure 7**, above, the transition, physical, and combined stresses to the market portfolio under the mean and severe scenarios over a 15-year projection time horizon.

From here there are several possibilities to extend this to a real investable asset class (e.g., equities). Perhaps the simplest is to use historical data to determine the value of β_{AC} to the market portfolio from the asset class returns R_{AC} and the market portfolio returns R_{market}:

$$\beta_{AC} = \frac{cov(R_{AC}, R_{market})}{Var(R_{market})}$$

However, relying on historical data may not be the most appropriate methodology, because in this case we should use an assessment of an asset class's exposure to shocks due to physical and transition risk rather than the general market movements that β represents. The approach we propose is to use expert judgments about asset classes and sectorial exposures to form different β values for each type of risk. These are applied to the physical and transition parts of the generated climate scenario shocks for the market portfolio and then combined into a final shock to the asset class under consideration. Because we have separate terms for physical and transition risk, we can define exposures for each type of risk, β_{phys}, and β_{tran}, for any given asset class.

The expert judgments that we use to set these exposures include using the equity sector carbon betas from the CARIMA model[38] to set β_{tran} to reflect asset class exposures to transition risks. Similarly, we use physical risk scores to determine the relative vulnerabilities of equity sectors to the physical risk shocks. For fixed-income asset classes, we use market β values from the 2008 period as representative of the response of these asset classes to stressed market conditions and set $\beta_{phys} = \beta_{tran} = \beta$.

We note here that the physical and transition risk exposure will differ for various regulated firms based on precise exposures to different issuers within a sector (e.g., a coal-heavy allocation will have different exposures to transition risk than a renewables-heavy allocation). To some extent, this is part of the model that individual insurers, pension funds, and financial institutions must set based on their own assessment of the risk profile.

For a range of 15 different asset classes covering fixed income and equity sectors, the mean and severe SSP-5 scenario stresses that we have derived are shown in **Figures 8** and **9** (following page). These represent the yearly shock to the asset class returns that should be applied to assess the impact of the SSP-5 warming scenario on each asset class.

37 R. Doeswijk, T. Lam, L. Swinkels, Historical Returns of the Market Portfolio, The Review of Asset Pricing Studies (2019).

38 Carbon Risks and Financed Emissions of Financial Assets and Portfolios, Carbon Risk Management (CARIMA; funding code: 01LA1601).

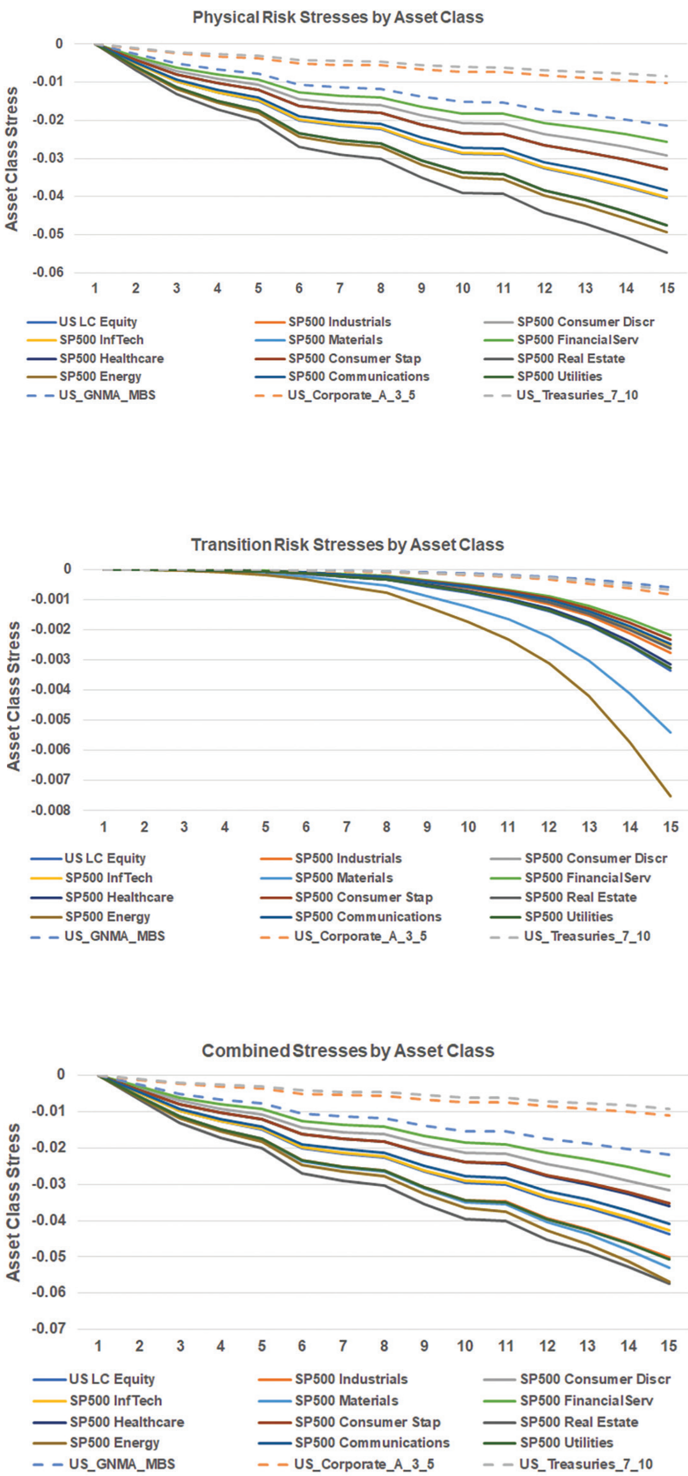

Figure 8 Estimated impact of the SSP5 scenario on market returns of different asset classes over the next fifteen years. The stress values shown are the mean projected damage function from the integrated physical and transition risks model. (©2022 Conning, Inc.).

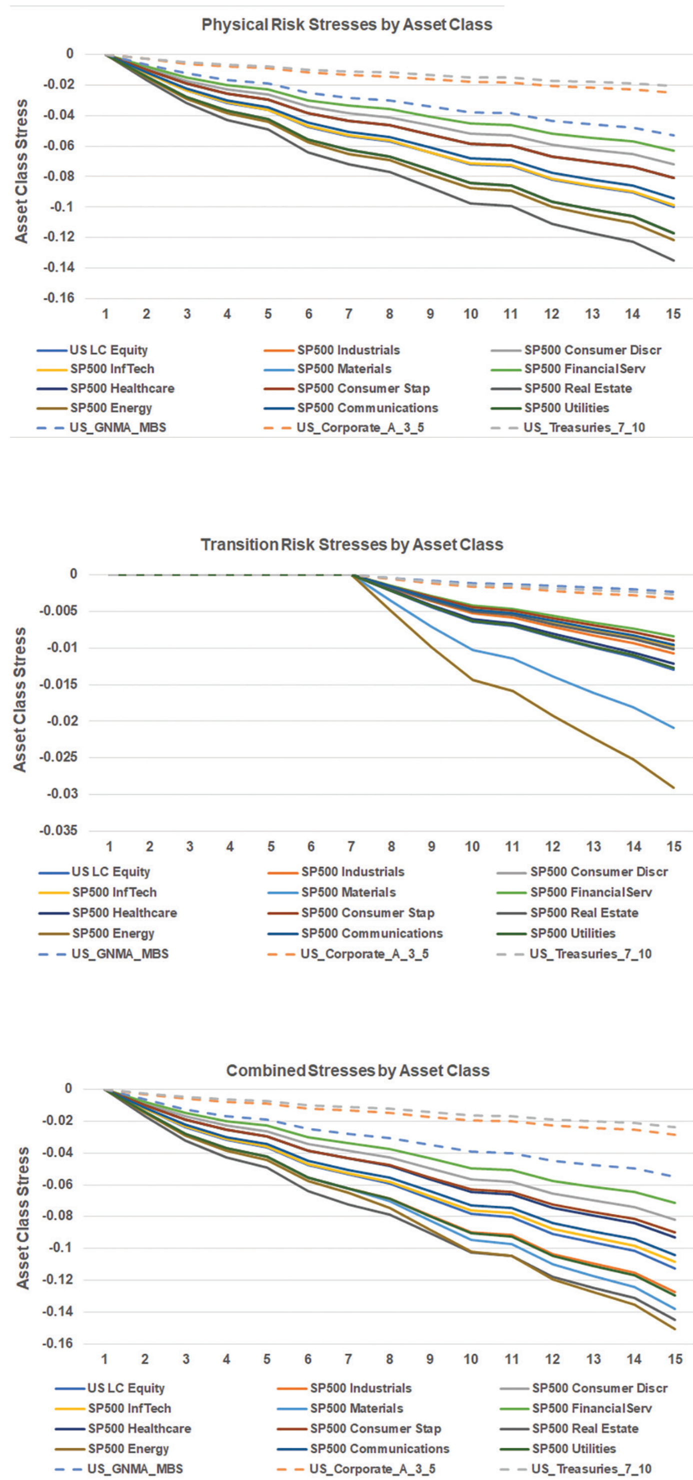

Figure 9 Estimated impact of the SSP5 scenario on market returns of different asset classes over the next fifteen years. The stress values shown are the lower 5th percentile of the projected damage function from the integrated physical and transition risks model. (©2022 Conning, Inc.).

Analysis and Reporting Using the Model-Defined Stresses

Using the stresses derived in the last section, we employ the Climate Risk Analyzer[39] and GEMS to quantify the impact on the future market value of a portfolio of mortgage-backed securities, a fixed income portfolio (70% Treasuries, 30% Corporate Bonds), a diversified equity portfolio (US large cap index), and equity-exposed sectors. Equity-exposed sectors comprise the five sectors with the largest defined stresses under the scenario. These sectors are Energy, Materials, Real Estate, Utilities, and Industrials. Together, GEMS and the Climate Risk Analyzer simulate the future market value of holdings in different asset classes under a current best-estimate scenario, with the distribution conditioned on a defined climate scenario from the model discussed below. The best-estimate or base scenario encompasses assumptions on market risk and returns broadly aligned with the last 20 years of experience.

With the mean and severe climate scenarios defined, the process that will be used to analyze each asset allocation is as follows:

1. Project the asset allocation market value distribution forward in time using a stochastic market risk model to capture a "best estimate" of risk and return at future time horizons.
2. Run the same stochastic simulation of the market value, adjusting all returns with the climate scenario stress at each point in time using the Climate Risk Analyzer.
3. Define a quantity, called Excess Climate Risk (ECR), which is the difference between a measured statistic (e.g., mean or 1st percentile of the market value distribution) under the best estimate (from 1) and stressed (from 2) simulations.
4. Report the impact on current risk models captured by the Excess Climate Risk across several distribution statistics.

Figures 10 and **11** (following pages) respectively show the impact of the mean and severe SSP-5 scenarios on a starting allocation of USD 1 million for the four different asset allocations. We give the best estimate distribution at the 5-, 10-, 15-, and 30-year future time horizon in blue and the same distribution conditioned on the SSP-5 climate scenario in green. The expected market value of the holdings at future time horizons under the best estimate and the SSP-5 mean and severe scenarios are also shown in numerical form in **Table 2.**

39 https://www.conning.com/software-and-services/climate-risk-analysis

Expected Market Value Projections	5-year			10-year			15-year			30-year		
	Best Est. MV	SSP-5 MV Mean	SSP-5 MV Severe	Best Est. MV	SSP-5 MV Mean	SSP-5 MV Severe	Best Est. MV	SSP-5 MV Mean	SSP-5 MV Severe	Best Est. MV	SSP-5 MV Mean	SSP-5 MV Severe
Morgage-Backed Securities	951,053	920,242	876,560	1,093,851	989,690	852,192	1,325,820	1,089,109	806,459	2,490,813	1,202,826	386,753
Fixed Income	1,009,702	994,944	973,905	1,191,461	1,138,771	1,063,464	1,477,231	1,349,545	1,171,572	2,998,285	2,097,783	1,229,177
Equity Diversified	1,386,462	1,307,794	1,199,986	2,045,510	1,705,304	1,286,923	3,073,976	2,130,201	1,176,902	10,692,168	2,433,653	224,037
Equity-exposed Sectors	1,197,094	1,117,349	1,021,632	1,531,303	1,251,350	924,552	1,996,399	1,358,468	706,718	4,533,626	1,218,994	79,752

Table 2 Expected (mean) market value of holdings in Mortgage-Backed Securities, Fixed Income, Diversified Equity, and Exposed Equity Sectors at the 5, 10, 15, and 30-year horizons. We assumed a starting market value of USD 1 Million for this analysis. Shown for each time horizon is the projected market value of holdings under the current best estimate of returns in each asset class, with the values based on the mean and lower 5th percentile (severe) of projected damage from the integrated model of physical and transition risks. (Prepared by Conning, Inc. Source: ©2022 Conning, Inc. using Conning Climate Risk Analyzer™ and GEMS® Economic Scenario Generator with hypothetical portfolio).

Discussions of Results

One of the significant criticisms of climate stress tests to date is that the impact at the short- and medium-term time horizons typically used for capital and strategic planning is too small. This statement leads to the false belief that climate risk is something that financial institutions need not worry about today. Our model, which explicitly includes a process to model the impact of tipping points, reveals why this view is a fallacy. Suppose we were to consider only the results from the mean impact scenario shown in Figure 10. In that case, the impacts over the next five and ten years on expected risk and return are indeed relatively small or at least within the normal range of other market risks. However, considering the severe impact scenario in Figure 11, we see much more significant risks in the medium term.

Conning and University of Maryland SSP-5 Mean Impact Scenario

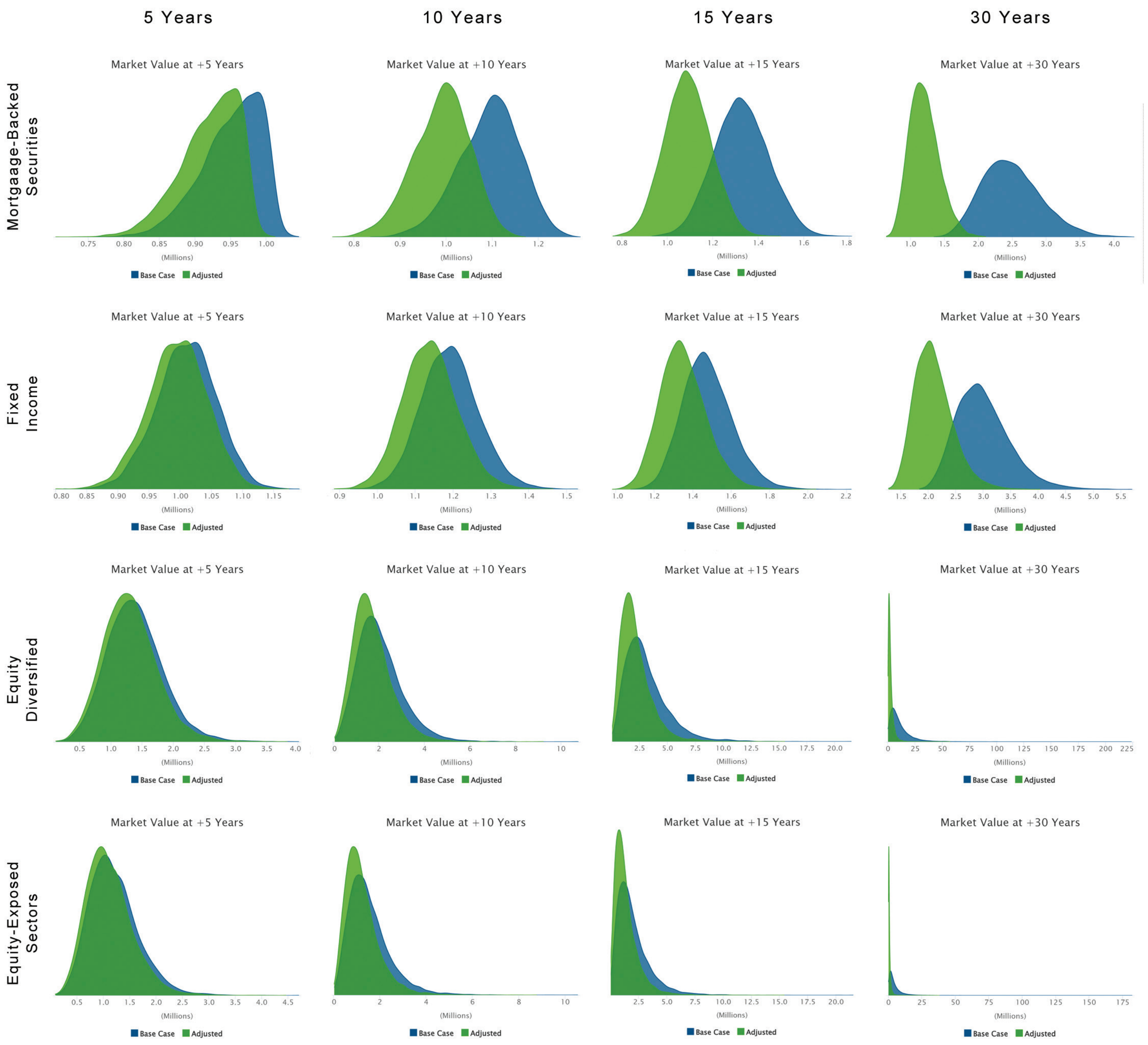

Figure 10 Simulated distributions of the market value of holdings in Mortgage-Backed Securities, Fixed Income, Diversified Equity, and Exposed Equity Sectors at the 5-, 10-, 15-, and 30-year horizons. This analysis uses a starting market value of USD 1 Million. The stress values are the mean projected damage function from the integrated physical and transition risks model. (Prepared by Conning, Inc. Source: ©2022 Conning, Inc. using Conning Climate Risk Analyzer™ and GEMS® Economic Scenario Generator with hypothetical portfolio).

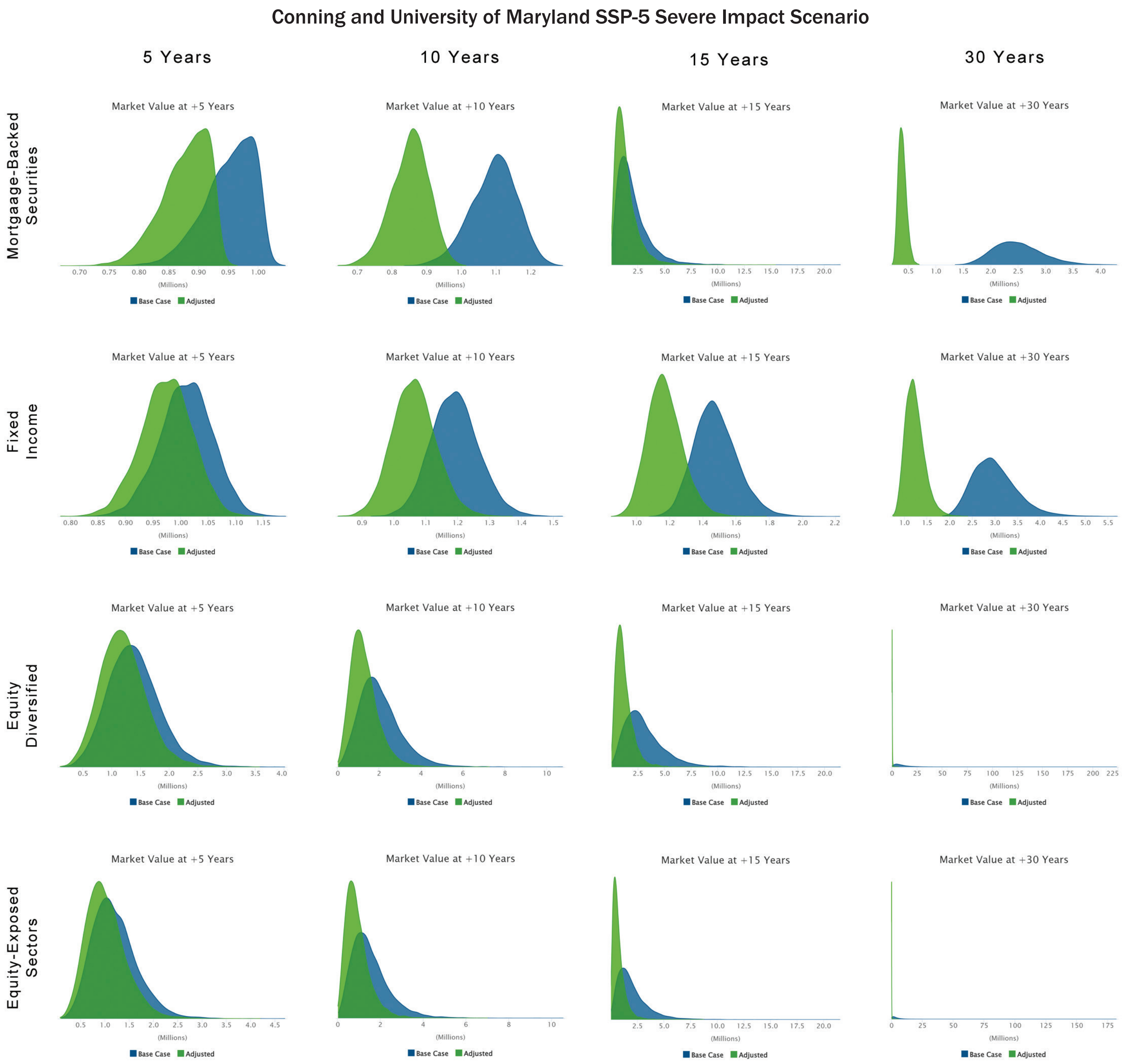

Figure 11 Simulated distributions of the market value of holdings in Mortgage-Backed Securities, Fixed Income, Diversified Equity, and Exposed Equity Sectors at the 5-, 10-,15-, and 30-year horizons. We assumed a starting market value of USD 1 Million for this analysis. The stress values are the lower 5th percentile projected damage function from the integrated physical and transition risks model. (Prepared by Conning, Inc. Source: ©2022 Conning, Inc. using Conning Climate Risk Analyzer™ and GEMS® Economic Scenario Generator with hypothetical portfolio).

Considering real estate, which we see from Figures 8 and 9 is the asset class with the highest impact under this scenario, we can calculate that, under the mean scenario, the model implies a reduction or shock to market returns of -8.3% cumulatively over the next five years and -25.7% cumulatively over the next ten years. However, under the severe scenario, the impact on this asset class at the 5th percentile level of the simulated damage function might be as high as -20.5% and -64.9% cumulatively over the next 5 and 10 years, respectively.

Considering the expected market value projections in Table 2, we can see the magnitude of the impacts more precisely. For instance, our best estimate of the market value of an initial USD 1,000,000 allocation to mortgage-backed securities in ten years is USD 1,093,851. However, this cumulative +9.4% return (= 100 x 1,093,851 / 1,000,000 - 1) under the defined scenarios converts to a 1% loss in the mean SSP-5 scenario (= 100 x 989,690 / 1,000,000 - 1) and could potentially exceed a loss of 14.8% under the severe scenario (=100 x 852,192 / 1,000,000 - 1). It is interesting to note that this is broadly aligned with the conclusions of other independent studies[40]. The inclusion of a jump process parameterized to replicate models of tipping point damage can give a much more complete view of the climate risks to the financial system, encompassing severe case outcomes and the average or expected path. By applying an extreme climate scenario to the current risk and return models, it is possible to understand the impact on the distribution of market returns and ultimately measure market Value-at-Risk conditioned on the climate scenario. The Excess Climate Risk—the difference in a metric under the best estimate and stressed climate scenario—also gives a useful and comparable metric of the scenario's effect, which is less sensitive to each organization's assumptions of future expected returns than VaR alone. For instance, the excess risk of fixed income securities at the 10-year horizon is given by $1,191,461 - $1,063,464 = $127,997, reflecting the expected loss for this asset class relative to the current best estimate in the instance that the severe scenario plays out.

The equity-exposed sectors are particularly affected by transition risks. However, their operations and cost-base may also be adversely affected by the physical impacts of climate change. For this asset class, we see that under the mean SSP-5 scenario, there is still scope to make a positive nominal return on the initial $1 million investment, albeit at a significantly reduced level over the entire thirty-year horizon considered. Under the severe scenario, however, where physical impacts lead to policy actions that increase the cost of carbon, losses start to accrue shortly after the five-year investment horizon. By the ten-year horizon, the best-estimate expected cumulative return of 53.1% becomes a loss of 7.5% under this severe scenario. Within thirty years, the investment is effectively gone. This result assumes that the investor holds the allocation and that the firms do not themselves restructure and diversify. Given these assumptions, the losses calculated would seem reasonable at longer horizons when considering the potential for many players in these sectors to become obsolete and accumulate stranded assets. This result further indicates the need for financial institutions to consider future management actions today and assess risk under a range of dynamic balance sheet options.

Concluding Remarks

The demand from regulators for insurance and pension firms to perform and report on climate risks to the investment side of the balance sheet continues to gather pace. However, understanding the potential impact of these risks at the short- and medium-term horizons that are relevant to risk management and strategic planning has been hampered by the long-term nature of regulatory exercises to date. In many cases, organizations are unable to define and explore the range of possible outcomes that a particular level of global warming might engender because of the complexity and high knowledge barrier required to implement a model of climate risk. These difficulties are exacerbated because current climate stress tests are dependent on climate model and IAM outputs where empirical linkages between physical outputs (e.g., greenhouse gas emissions) and economic and financial factors are not yet well-established. Further, the climate economics models available embed significant uncertainty in parameter estimates and do not include the possibility of high-impact low-probability events brought about by tipping points.

In this paper we have presented a model that integrates financial damage assessments for physical and transitions risks and have used it to generate stress tests for a range of asset classes. We have focused on the five- to ten-year horizon, which is more compatible with the ORSA and other reporting requirements than the current decades-long scenarios proposed by many organizations to date. The model embeds a simplified form of more complex models and has parameters that are physically interpretable, which is key to setting parameter values for future events which are unprecedented in the historical record. This is also important if the models are to be adapted in response to local assets and new climate-related scientific and corporate information.

Although the model has some limitations, as do all models, the current methodology addresses many of the criticisms of climate stress testing exercises to date. These criticisms (cited in several of the references in this paper)[41] include;

- the scenarios are not severe enough,
- models do not account for low-probability high-impact climate-related events such as tipping points,
- models do not consider the interaction of physical and transition risks, and
- models lack geophysical basis and transparency in the defining methodology.

40 Unpriced costs of flooding: An emerging risk for homeowners and lenders By David D. Evans, Leighton A. Hunley, and Brandon Katz (KatRisk LLC), 28 January 2022. In this paper, the high-risk scenario implied MBS credit losses of $72.1bn from an outstanding pool of $7.9tln. Over a 10-year horizon this would yield (1+0.009)10-1=-9.5% compounded loss.

41 See, for example, Dietz. S., 2021 op. cit., Palmer, T. 2019 op. cit., Pindyk, 2017. op. cit, and Folini, D. 2021 op. cit.

Our approach has the following innovative features:

1. We model physical risk as a driver of transition risk through increases in the cost of carbon. This increase is proportional to the physical damages incurred.
2. The stochastic aspect of the damage function incorporates the uncertainty not captured in deterministic damage functions.
3. The approach includes a jump process in the physical damage function. This is highly significant in that it models the possible impact of climate tipping points with a geophysical basis. The effects on some asset classes described earlier show the significance of this feature.
4. The model requires only a scenario of increasing temperature anomalies. Such scenarios would typically come from an openly available source such as the Shared Socioeconomic Pathways. This approach simplifies defining a climate scenario and requires no "second-guessing" of what governments might do in the future regarding the cost of carbon.
5. Users can explore different assumptions by changing model parameters and selecting values based on current data, experience, and expert judgment, and they can investigate the sensitivity of financial damages to particular inputs (e.g., changes in public tolerance to physical risk through the threshold parameter, τ).

We used this model to generate implied damages as a fraction of GDP and then cascaded these down to individual asset classes. This process enabled us to define stresses to asset returns under the SSP-5 temperature increase scenario. We have also presented some analyses based on these stresses using the Climate Risk Analyzer.

In conclusion, our model will be highly effective in providing financial institutions and regulators with an executable framework to incorporate new information about the increasing risks from extreme weather and climate tipping points that may materialize in the next five to ten years.

Bio Summaries

Robert F. Brammer has a **Ph.D.** in mathematics from the University of Maryland. He is an Adjunct Research Professor in the Department of Finance and the Department of Atmospheric and Oceanic Science at the University of Maryland. Additionally, he is a Fellow of the American Meteorological Society and is the Chair of the Cleantech and Climate Change Committee of the American Bar Association.

Matthew Lightwood, Ph.D., is responsible for quantitative modeling and providing technical expertise to support prospective and new clients using the GEMS® Economic Scenario Generator and leads product management of the Climate Risk Analyzer™ software for Conning. Before joining Conning in 2010, he was a Senior Risk Consultant, where he was responsible for financial modeling, managing, and implementing large professional services projects for financial clients. Matthew is a graduate of the University of Manchester and University College London, where he earned a BSC (HONS) in Physics with Astrophysics and a Ph.D. in High Energy Particle Physics.

Clifford Rossi, Ph.D., is a Professor-of-the-Practice and Executive-in-Residence at the Robert H. Smith School of Business, University of Maryland. Before joining academia, he spent 25-plus years in the financial sector as a C-level risk executive at several top financial institutions and a federal-banking regulator. He has a Ph.D. in Financial Economics from Cornell University.

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