Virtual Seminar on Climate Economics

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Climate Linkers: Rationale and Pricing

Pauline Chikhani and Jean-Paul Renne

VSCE

March 24, 2021
Motivation

- We make a case for the emergence of a novel class of financial instruments indexed to climate-related variables (sea levels, temperatures, carbon concentrations).

- **Climate Linkers**...
  
  ... would not directly contribute to the fight against climate risks (i.e. \(\neq\) green bonds);
  
  ... would provide, by construction, hedging against long-term global temperatures, carbon concentrations, or sea levels.
1. We discuss the advantages of financial instruments (swaps, bonds, options) indexed to secular climate changes.

2. We develop a modeling framework that allows for the fast pricing of these long-term instruments (= tractable Integrated Assessment Model, IAM).
   Tractability $\Rightarrow$ possibility to look for parametrizations making the model consistent with recent climate science.

3. We explore the pricing of Climate Linkers (CL) and study the climate risk premiums (= insurance premiums) they would embed.
Temperature Indexed Swap (TIS)

Negociation

Settlement

Paid by protection buyer to protection seller

Paid by protection seller to protection buyer

Temperature Indexed Bond (TIB)

Debt instrument whose payoff at maturity \((t + h)\) is indexed to a given measure of temperature (or carbon concentration, or sea levels). Specifically:

\[
1 + \chi [T_{t+h} - \mathbb{E}_t(T_{t+h})],
\]

(\(\chi\) is a “leverage factor”)

Note: the payoff expectation is equal to 1.
Rationale behind Climate Linkers (CL)

Demand

- **Growing demand for (re)insurance against weather-related disasters**
  - Alternative Risk Transfer solutions (insurance-linked securities, CAT bonds).
  - But only specific areas and short maturities (for which climate is predictable).
- CL address **long-term and global risks** (e.g., index. to temperature in 2100).
- CL ≠ Environmental, Social, and Governance (ESG) fixed-income products, whose final payoffs are not indexed to climate.

Supply

- **Temperature-Indexed Bonds: Widening of governments’ investor basis.**
- Increase in govts’ exposure to climate risk. However:
  - 2nd-order compared to potential direct effect on public finances.
  - Consistent with role of “insurer of last resort” of govts (Bruggeman et al., 2010).
- Private issuance of TIBs: Natural issuers (Asset-Liability Management) = firms whose activity relates to climate-risk mitigation (e.g., renewable-energy producers).
Rationale behind Climate Linkers (CL): Information (1/2)

Informational content

- CL prices would make market participants reveal their expectations regarding future climate (akin to break-even inflation rates).
- Information captured in real-time, at high frequency.
- Extraction of expected trajectories of future temperatures from market quotes of temperature-indexed swaps or bonds (as done with inflation-linked bonds, Campbell and Shiller, 1996).
- In particular: natural way to gauge the perceived credibility and effectiveness of international commitments regarding the climate.
- Observed prices would help inform the computation of key economic variables:
  - Social Cost of Carbon (Weitzman, 2013; Nordhaus, 2017; van den Bremer and van der Ploeg, 2021);
  - Long-Term Discount Rates, and Climate Betas (Bauer and Rudebusch, 2021; Dietz et al., 2018; Gollier, 2021; Giglio et al., 2021);
  - Climate-Value-at-Risks (Dietz et al., 2016).
Rationale behind Climate Linkers (CL): Information (2/2)

Parametrization (Natural Sciences & Economic literature, IPCC) → (IAM) Model

- Macro-Clim. Scenarios
- Social Cost of Carbon
- NPV of long-dated climate-related payoffs

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Rationale behind Climate Linkers (CL): Information (2/2)

- Parametrization (Natural Sciences & Economic literature, IPCC)
- CL prices

(IAM) Model

- "market-augmented" Macro-Clim. Scenarios
- "market-augmented" Social Cost of Carbon
- NPV of long-dated climate-related payoffs (including CL prices)
**Model**


- Stochastic IAMs: Jensen and Traeger (2014); Bansal et al. (2016); Cai and Lontzek (2019).

- In spite of progress in terms of numerical solution methods (Daniel et al., 2019; Barnett et al., 2020; van den Bremer and van der Ploeg, 2021), no “instant results” to solve IAMs with stochastic disasters.

  ⇒ Challenging to look for model parametrizations that reproduce certain targets (moments).

- **The approach in a nutshell:**

  Make the model conditionally affine (also done by Traeger, 2021).

  NB: Different from linearization around a steady state (large uncertainty).

  ⇒ Closed-form solutions for conditional moments (and distributions).
Stochastic Affine DICE Model: Overview

- Production
- Consumption & Investment
- Mitigation
Stochastic Affine DICE Model: Overview

Production

+ 

Consumption & Investment

Mitigation

+ 

CO₂ Emissions

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Stochastic Affine DICE Model: Overview

Production

Consumption & Investment

Mitigation

$\text{CO}_2$ Emissions

Temperature

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Stochastic Affine DICE Model: Overview

Production

Consumption & Investment

Mitigation

CO₂ Emissions

Temperature

"Tipping point"
(Lemoine and Traeger, 2016)
(Steffen et al., 2018)
(Dietz et al., 2020)
Stochastic Affine DICE Model: Overview

Production

Consumption & Investment

Mitigation

CO₂ Emissions

Temperature

Damages

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Stochastic Affine IAM Model: Main ingredients

- Production function:
  \[ Y_t = A_t K_t, \quad \text{with} \quad A_t = \bar{A} + \sigma A \eta A,t, \]

- Capital dynamics (Gomes et al., 2019; Miller et al., 2020):
  \[
  \begin{align*}
  \text{Planned capital} & \quad K^*_t = (1 - \text{dep})K_{t-1} + \text{Inv}_t, \\
  \text{Effective capital} & \quad K_t = \exp(-D_t)K^*_t, 
  \end{align*}
  \]
  where \( D_t = 0 \) (no disaster), or \( D_t > 0 \) (disaster).

- Budget constraint:
  \[ Y_t = C_t + \text{Inv}_t + \Psi_t, \]
  where \( \Psi_t \) is investment in mitigation technologies.

- Disaster shocks are more likely when temperature is higher:
  \[ D_t \sim \gamma_0(\ell_{D,0} + \ell_{D,1}T_{AT,t-1}, \mu_D), \]
  \( \gamma_0 \) distri \( \approx \) Poisson with random jumps (Monfort et al., 2017). In particular:
  \[ \mathbb{P}_{t-1}(D_t > 0) \approx \ell_{D,0} + \ell_{D,1}T_{AT,t-1}. \]
Mitigation

- Investment in mitigation technologies:

\[ \Psi_t = \mu_t^2 BC_t Y_t. \]

\( \mu_t \): mitigation (or emission control) rate; \( BC_t \) exogen. \( \downarrow \) over time.

- Agents dynamically decide on \( C_t/Inv_t \), but decide on future \( \mu_t \)s on date \( t = 0 \). Parametric trajectory:

\[ \mu_t = \min \left[ \exp (-\theta_a + \theta_b \times t); 1 \right]. \]

- Up to mitigation \( (1 - \mu_t) \), industrial emissions grow as planned capital:

\[ \mathcal{E}_{Ind,t} = (1 - \mu_t) \exp \left[ \sum_{i=1}^{t} (\mu_{k,i} + \sigma_{k,i} \eta_{A,i}) \right], \]

proxied by [using \( \exp(\mu + \sigma \varepsilon) \approx \exp(\mu + \sigma^2/2)(1 + \sigma \varepsilon) \)]:

\[ \mathcal{E}_{Ind,t} = (1 - \mu_t) \exp \left[ \sum_{i=1}^{t} \left( \mu_{k,i} + \frac{\sigma_{k,i}^2}{2} \right) \right] \left[ 1 + \sum_{i=1}^{t} \sigma_{k,i} \eta_{A,i} \right]. \]
Climate block (1/2)

- Atmospheric temperature depends on radiative forcings:

\[
T_{AT,t} = T_{AT,t-1} + \xi_1 \left( F_t - \frac{\tau}{\nu} T_{AT,t-1} - \xi_2 [T_{AT,t-1} - T_{LO,t-1}] \right).
\]

- Radiative forcings depend on atmospheric carbon concentration:

\[
F_t = \tau \log_2(m_0) + \frac{\tau}{\log(2)m_0} \left( \frac{M_{AT,t}}{M_{PI}} - m_0 \right) + F_{EX,t} + \sigma_f \eta_{f,t}.
\]

- Carbon concentrations flow between reservoirs (AT, atmosphere, LO, lower ocean, UP, upper ocean), and depend on emissions (\(E_t\)):

\[
M_t = \begin{bmatrix}
M_{AT,t} & 0 & \cdots & 0 \\
M_{UP,t} & \cdots & 0 \\
M_{LO,t} & \cdots & \cdots & \cdots \\
0 & \cdots & \cdots & \cdots \\
\end{bmatrix} = \begin{bmatrix}
\cdot & \cdot & 0 \\
\cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
0 & \cdot & \cdot & \cdot \\
\end{bmatrix} M_{t-1} + \frac{\Delta t}{3.666} \begin{bmatrix}
E_{t-1} \\
0 \\
0 \\
0 \\
\end{bmatrix}.
\]
Climate block (2/2)

- Positive feedback loop:

\[
\begin{align*}
\mathcal{E}_t & \rightarrow M_t \rightarrow T_t \\
\leftarrow N_t & \leftarrow 
\end{align*}
\]

- More precisely:

\[
\mathcal{E}_t = \mathcal{E}_{Ind,t} + \mathcal{E}_{Land,t} + N_t.
\]

- The higher the temperature, the more likely feedback effects:

\[
N_t \sim \gamma_0(\rho_N N_{t-1} + \ell_{0,N} + \ell_{1,N} T_{AT,t-1}, \mu_N).
\] (1)

- If one of these loops is triggered, the probability of triggering the next one jumps \(\Rightarrow\) “tipping point” mechanisms (Lemoine and Traeger, 2016; Steffen et al., 2018; Dietz et al., 2020).
IAM extension: Sea level rise (SLR)

- One of the most critical climate change’s dangers (e.g., Hauer et al., 2016; Desmet et al., 2021).

- Relationship between temperatures and sea level: Rahmstorf (2007), Rahmstorf (2010), Kopp et al. (2016), and Mengel et al. (2018).

- Two principal channels of SLR: (a) melting of ice sheets, (b) the volume of the ocean is expanding as the water warms.

- “Semi-empirical” models: dynamic response of SLR to temperatures.

- Specification from Vermeer and Rahmstorf (2009):

  \[ H_t = H_{t-1} + \Delta t \times a_{SAT}(T_{AT,t} - T_{0,S}) + b_{SAT}\Delta T_{AT,t}, \]  

  where \( H_t \) measures global mean sea level, and \( T_{0,S} \) is the average atmospheric temperature for the period from 1951 to 1980.
Stochastic Affine IAM Model: Solution

- Repr. agent with Epstein-Zin preferences (unit EIS, risk aversion $\gamma > 1$).
- Simple solution. Resulting consumption growth process:
  \[ \Delta c_t = \mu_{c,t} + \sigma_{c,t} \eta_{A,t} - D_t, \]
  where $\mu_{c,t}$ and $\sigma_{c,t}$ are deterministic functions of time.

Dynamics of the state vector $X_t$ (macro + climate variables)

Stochastic affine dynamics around a deterministic trend. Laplace transform:

\[ E_t[\exp(u'X_{t+1})] = \exp(a_t(u) + b_t(u)'X_t), \]

where $a_t$ and $b_t$ are available in closed form.

⇒ Tractability of the model.

In particular, simple derivation of conditional distributions, at any horizon (based on Fourier transforms, as in, e.g., Duffie et al., 2000).
Calibration

- Calibration approach exploits the tractability of the model.
- Closed-form solutions to:
  - utility and Stochastic Discount Factor (s.d.f., $M_{t,t+1}$);
  - first- and second-order (un/conditional) moments of state variables.

Table 1: Targeted and model-implied moments (in 2100)

<table>
<thead>
<tr>
<th>Moment</th>
<th>Target</th>
<th>Model-implied</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mathbb{E}(T_{AT, 2100})$</td>
<td>3.50°C</td>
<td>3.34°C</td>
<td>RCP4.5+RCP6.0</td>
</tr>
<tr>
<td>Std($T_{AT, 2100}$)</td>
<td>0.25°C</td>
<td>0.34°C</td>
<td>RCP4.5+RCP6.0</td>
</tr>
<tr>
<td>$\mathbb{E}$ (contribution of FL to GMST)</td>
<td>0.25°C</td>
<td>0.27°C</td>
<td>Burke et al. (2012)</td>
</tr>
<tr>
<td>$\mathbb{E}$ (increase in $Cum_E$ due to FL)</td>
<td>188GtCO$_2$</td>
<td>190GtCO$_2$</td>
<td>Burke et al. (2012)</td>
</tr>
<tr>
<td>Slope of $Cum_D$ on GMST</td>
<td>–0.12</td>
<td>–0.12</td>
<td>Burke et al. (2015)</td>
</tr>
<tr>
<td>Long-term rate target</td>
<td>1.00%</td>
<td>0.99%</td>
<td>US Treasury</td>
</tr>
<tr>
<td>$\mathbb{E}(H_{2100})$</td>
<td>0.45m</td>
<td>0.53m</td>
<td>RCP4.5+RCP6.0</td>
</tr>
<tr>
<td>Standard Deviation of $H_{2100}$</td>
<td>0.10m</td>
<td>0.05m</td>
<td>Mengel et al. (2016)</td>
</tr>
</tbody>
</table>

Note: RCP stands for Representative Concentration Pathway.
Expected Atmospheric Temperature Path and Distributions

(a) – Trajectory of atm. temperature

(b) – Trajectory of atm. temperature including Risk–Premium

(c) – P.d.f. of atm. temperature in 2100

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Expected Global Mean Sea Level

(a) – Trajectory of global sea level rise

(b) – Trajectory of global sea level rise including Risk–Premium

(c) – P.d.f. of global sea level rise in 2100

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Expected Carbon Concentration Path and Distributions

(a) – Trajectory of carbon concentration in the atmosphere
- RCP4.5
- RCP6.0

(b) – Trajectory of carbon concentration in the atmosphere including Risk–Premium

(c) – P.d.f. of emissions in 2100
- Physical p.d.f.
- Risk–Adjusted p.d.f.
- Mean
- Median

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Closed-Form Solutions

- Tractability of the model exploited at the calibration stage (supra).
- Asset-pricing analysis also benefits from closed-form formulas.
- Formulas for date-$t$ prices of generic payoffs (settled on $t + h$):

$$
\omega' X_{t+h} \quad \text{and} \quad (\omega' X_{t+h}) \mathbb{1}_{\{a' X_{t+h} < b\}} ,
$$

where $X_t$ is the state vector.

$\Rightarrow$ Building on these prices, closed-form solutions to temperature-indexed swaps, bonds, and options (and social cost of carbon, SCC).

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Temperature Indexed Bond (TIB)

Payoff at maturity \((t + h)\):

\[ 1 + \chi [T_{t+h} - \mathbb{E}_t(T_{t+h})], \]

where \(\chi\) is a “leverage factor”.

- If agents were not risk-averse, TIB prices would satisfy (maturity = \(h\)):

\[ P_{t,h}^{rf} = P_{t,h}^{TIB}, \]

with \(P_{t,h}^{rf} = \mathbb{E}_t(M_{t,t+h}),\) price of riskfree bond (same expected payoffs: 1).

- General case:

\[ P_{t,h}^{TIB} = P_{t,h}^{rf} + \chi \text{prem}_{t,h}, \quad \text{with} \quad \text{prem}_{t,h} = \frac{\text{Cov}_t[T_{t+h},M_{t,t+h}]}{\mathbb{E}_t[M_{t,t+h}]} \]

⇒ If higher temperature = “bad states of the world” (high marginal utility), then

\[ \left( P_{t,h}^{TIB} - P_{t,h}^{rf} \right) > 0. \]

“Risk-adjusted distributions” are right-shifted.
Swaps and Temperature-Indexed Bonds

(a) – Term structures of Temperature–Indexed Swap rates

(b) – Term structures of Temperature–Indexed Bonds yields
Digital Options

Concluding remarks

- Climate Linkers (CL) = long-term financial instruments whose payoffs are indexed to climate-related variables.
- Because agents are averse to climate risks, the pricing of CL would embed climate-risk premiums.
- CL would offer a public good by making market participants reveal their (risk-adjusted) expectations regarding future climate; akin to inflation-linked products.
- Necessary condition for development of a CL market: initial issuance of TIBs by governments (as for inflation-linked markets).
- First issuances: prices affected by “novelty premium.”
References I


References II


References III


“It is widely acknowledged that the proper role of the government is to provide public goods, and the demonstration by example of the potential for new financial markets and instruments is really a public good. […] Any firm which took on the public relations effort needed to first issue private indexed bonds would not be able to appropriate much of the societal benefits to doing so.” (Campbell and Shiller, 1996)
Simulations of Shocks $D_t$ and $N_t$
Social Cost of carbon = Willingness to pay to reduce carbon emission by one ton.

Marginal rate of substitution between atm. carbon concentration and $C_t$:

$$SCC_t = -\frac{\partial U_t}{\partial M_{AT,t}} / \frac{\partial U_t}{\partial C_t}.$$ (3)
Risk Premium

(a) – Temperature expectations

(b) – Share of risk premium in swap rate

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Risk Premium

![Graph showing the relationship between temperature anomaly and disaster magnitude.

The graph displays two lines:
- The blue line represents the expected temperature anomaly ($T_{at}$) in 2100.
- The orange line represents the swaps price ($T^S$) in 2100.

The x-axis represents the disaster magnitude ($\mu_D$), ranging from 0.04 to 0.08.

The y-axis represents the temperature anomaly ($T_{at}$), ranging from 3.0 to 3.6.

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Climate Linkers: Rationale and Pricing

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## Table 2: SCC comparison

<table>
<thead>
<tr>
<th>Study</th>
<th>SCC (U.S. $ per tC)</th>
<th>Tipping points</th>
<th>Stochastic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nordhaus (2017)</td>
<td>113</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stern (2007)</td>
<td>312</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jensen and Traeger (2014)</td>
<td>[40;70]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Barnett et al. (2020)</td>
<td>[240;411]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cai and Lontzek (2019)</td>
<td>[40;100]</td>
<td>✔</td>
<td></td>
</tr>
<tr>
<td>Bansal et al. (2016)</td>
<td>[4;104]</td>
<td>✔</td>
<td></td>
</tr>
<tr>
<td>Lemoine and Traeger (2014)</td>
<td>[37;55]</td>
<td>✔</td>
<td></td>
</tr>
<tr>
<td>van den Bremer and van der Ploeg (2021)</td>
<td>146</td>
<td></td>
<td></td>
</tr>
<tr>
<td>This paper</td>
<td>167</td>
<td>✔</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports different SCC estimates. Cited studies differ along many dimensions, the last three columns highlight particularly important ones.
Earth is composed of an unknown number of feedback loops (FL), positive or negative.

- Negative FL: absorption of greenhouse gases.
- Positive FL: amplification of positive imbalances in radiative forcings.

Positive FL: (a) release of tons of methane trapped in the permafrost, and (b) acidification of oceans.

If one of these loops is triggered, the probability of triggering the next one jumps ⇒ “tipping point” mechanisms (Lemoine and Traeger, 2016; Steffen et al., 2018; Dietz et al., 2020).

In our econometric specification: the probability of having a non-zero $N_t$ is typically small, but if it happens (i.e. when $N_t$ jumps): ↗ carbon concentration ⇒ ↗ temperature ⇒ . . .

= “Self-excitation”, as in Hawkes (1971) processes (applications to financial contagion, e.g., Aït-Sahalia et al., 2015).
Gamma-zero distribution

Definition

The non-negative r.v. $X \sim \gamma_0(\lambda, \mu)$, $\lambda > 0$ and $\mu > 0$, if

$$X \mid Z \sim \gamma_Z(\mu) \quad \text{with} \quad Z \sim \mathcal{P}(\lambda)$$

$$\Rightarrow \quad \mathbb{P}(X = 0) = \mathbb{P}(Z = 0) = \exp(-\lambda).$$
Decrease in consumption of about 50% for a 4-degree increase in $T$.

Regression slope of cumulated effects of disasters on consumption of $-50%/4$.

Model-implied equivalent: Population slope $= \frac{\text{Cov}(\text{Cum}D_{t+H},T_{t+H})}{\text{Var}(T_{t+H})}$. 

Figure 1: Burke et al. (2015, Figure 5.d)
Calibrating feedback effects

- Possibilities of feedback loops (FL) amplifying the positive imbalances in radiative forcings. (May give rise to “tipping points”.)

- Examples of FL: (a) release of tons of methane trapped in the permafrost, and (b) acidification of oceans.

- Some studies aim at estimating the specific effect of FL on carbon release and temperatures (Burke et al., 2012).

- In our model, we can compare model-implied expected emissions with FL ($\mu_N > 0$ in eq. 1) and without FL ($\mu_N = 0$ in eq. 1):

\[
\begin{align*}
\text{Emission effect of FL} & = \mathbb{E}_t(CumE_{t+H}) - \mathbb{E}_t^{noFL}(CumE_{t+H}) \\
\text{Temperature effect of FL} & = \mathbb{E}_t(T_{t+H}) - \mathbb{E}_t^{noFL}(T_{t+H})
\end{align*}
\]
Mitigation rate $\mu_t$

![Graph showing mitigation rate over years with two lines representing different studies: Present study and DICE. The x-axis represents years from 2050 to 2200, and the y-axis represents mitigation rate from 0.2 to 1.0. The graph shows a sharp increase in mitigation rate after 2050, reaching 1.0 by 2200 for both studies.](image-url)
(a) – Relationship between radiative forcings and atmospheric carbon concentration

(b) – Atmospheric carbon concentration p.d.f.
Equilibrium Climate Sensitivity (ECS) uncertainty

Figure 2
Climate sensitivity uncertainty. Histogram (red) and normal density approximation (blue) for the climate sensitivity parameter $\beta$ across models. The climate sensitivity parameter is in units of degrees centigrade per teraton carbon. Figure based on evidence reported in Figure 3A by MacDougall, Swart, and Knutti (2017) (© American Meteorological Society, used with permission) and constructed with data provided by the authors.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Notation</th>
<th>Equation</th>
<th>Value</th>
<th>Unit/Note</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average TFP</td>
<td>$A$</td>
<td>(1.7)</td>
<td>0.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Standard deviation of the TFP shock</td>
<td>$\sigma_A$</td>
<td>(1.7)</td>
<td>0.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average for approximation term</td>
<td>$m_0$</td>
<td>(32)</td>
<td>1168/607 - 1</td>
<td></td>
<td>CDICE + IPCC</td>
</tr>
<tr>
<td>Rate of preference for present</td>
<td>$\delta$</td>
<td>(37)</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk aversion</td>
<td>$\gamma$</td>
<td>(37)</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Carbon emissions from land 2015</td>
<td>$\varepsilon_0$</td>
<td>(21)</td>
<td>2.6</td>
<td>GtCO₂ per year</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Decline rate in land emissions (Eq. 21)</td>
<td>$\rho$</td>
<td>(21)</td>
<td>0.115</td>
<td>per period</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Equilibrium concentration in atmosphere</td>
<td>$\text{mateq}$</td>
<td>(33)</td>
<td>607</td>
<td>GtC</td>
<td>CDICE</td>
</tr>
<tr>
<td>Equilibrium concentration in upper strata</td>
<td>$\text{mueq}$</td>
<td>(33)</td>
<td>600</td>
<td>GtC</td>
<td>CDICE</td>
</tr>
<tr>
<td>Equilibrium concentration in lower strata</td>
<td>$\text{mleq}$</td>
<td>(33)</td>
<td>1772</td>
<td>GtC</td>
<td>CDICE</td>
</tr>
<tr>
<td>2015 forcings of non-CO₂ GHG</td>
<td>$\phi_0$</td>
<td>(22)</td>
<td>0.5</td>
<td>Wm-2</td>
<td>DICE2016</td>
</tr>
<tr>
<td>2100 forcings of non-CO₂ GHG</td>
<td>$\phi_1$</td>
<td>(22)</td>
<td>1</td>
<td>Wm-2</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Preindustrial concentration of carbon in the atmosphere</td>
<td>$M_{PI}$</td>
<td>(32)</td>
<td>607</td>
<td>GtC</td>
<td>CDICE</td>
</tr>
<tr>
<td>Carbon cycle parameter between atmosphere and upper ocean</td>
<td>$\phi_{12}$</td>
<td>(33)</td>
<td>0.053</td>
<td></td>
<td>CDICE</td>
</tr>
<tr>
<td>Carbon cycle parameter between upper and lower ocean</td>
<td>$\phi_{23}$</td>
<td>(33)</td>
<td>0.0042</td>
<td></td>
<td>CDICE</td>
</tr>
<tr>
<td>Climate equation coefficient for upper level</td>
<td>$\xi_1$</td>
<td>(34)</td>
<td>$\Delta t \times 0.137$</td>
<td></td>
<td>CDICE</td>
</tr>
<tr>
<td>Transfer coefficient upper to lower stratum</td>
<td>$\xi_2$</td>
<td>(34)</td>
<td>$\Delta t \times 0.10001$</td>
<td></td>
<td>CDICE</td>
</tr>
<tr>
<td>Transfer coefficient for lower level</td>
<td>$\xi_3$</td>
<td>(35)</td>
<td>$\Delta t \times 0.00689$</td>
<td></td>
<td>CDICE</td>
</tr>
<tr>
<td>Forcings of equilibrium CO₂ doubling</td>
<td>$\tau$</td>
<td>(32)+(34)</td>
<td>3.45</td>
<td>Wm-2</td>
<td>CDICE</td>
</tr>
<tr>
<td>Equilibrium temperature impact</td>
<td>$v$</td>
<td>(34)</td>
<td>3.25</td>
<td>°C per doubling CO₂</td>
<td>CDICE</td>
</tr>
<tr>
<td>Decline rate of decarbonization</td>
<td>$\delta_\sigma$</td>
<td>(17)</td>
<td>-0.001</td>
<td>per period</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Carbon intensity 2010</td>
<td>$\sigma_0$</td>
<td>(17)</td>
<td>$e_0$</td>
<td>kgCO₂ per output 2005 USD 2010</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Industrial emissions in 2015</td>
<td>$e_0$</td>
<td>(17) + (2015)</td>
<td>35.85</td>
<td>GtCO₂ per year</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Initial world gross output in 2015</td>
<td>$q_0$</td>
<td>(29)</td>
<td>105.5</td>
<td>trillions of 2010 USD</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Initial emission control rate in 2015</td>
<td>$\mu_0$</td>
<td>(18)</td>
<td>0.03</td>
<td></td>
<td>DICE2016</td>
</tr>
<tr>
<td>Initial growth of sigma</td>
<td>$g_{\sigma,1}$</td>
<td>(17)</td>
<td>-0.0152</td>
<td>per year</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Initial cost decline backstop cost</td>
<td>$g_{back}$</td>
<td>(19)</td>
<td>0.025</td>
<td>per period</td>
<td>DICE2016</td>
</tr>
<tr>
<td>Exponent of control cost function</td>
<td>$\theta_2$</td>
<td>(20)+(23)</td>
<td>2.6</td>
<td></td>
<td>DICE2016</td>
</tr>
<tr>
<td>Persistence of the radiative forcings shock</td>
<td>$\Phi_{[2,2]}$</td>
<td>(26)</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Global surface temperature weights $[T_{AT}, T_{LO}]$</td>
<td>$w_{\text{weights}}$</td>
<td></td>
<td>[0.6, 0.4]</td>
<td></td>
<td>IPCC</td>
</tr>
<tr>
<td>Base Temperature (sea level equilibrium)</td>
<td>$T_{0,S}$</td>
<td>(36)</td>
<td>-0.375</td>
<td>°C, Baseline [1951-1980]</td>
<td>Vermeer and Rahmstorf (2009)</td>
</tr>
<tr>
<td>Coefficient attached to $T_{AT}$</td>
<td>$a_{SAT}$</td>
<td>(36)</td>
<td>0.0015</td>
<td>m per °C per year</td>
<td>Vermeer and Rahmstorf (2009)</td>
</tr>
<tr>
<td>Coefficient attached to $T_{AT}$</td>
<td>$b_{SAT}$</td>
<td>(36)</td>
<td>0.025</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital depreciation rate</td>
<td>$\text{dep}$</td>
<td>(1.7)</td>
<td>0.27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time step</td>
<td>$\Delta t$</td>
<td></td>
<td>5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: This table presents the parameters used in our baseline model. DICE16 refers to Nordhaus (2017). IPCC refers to IPCC (2014, Table 2.1). CDICE refers to Nordhaus et al. (2021)
Weather disaster losses rise as economies grow and climate changes. Nevertheless, economic losses have outpaced insured losses. Figure 7 compares the real (adjusted for inflation) growth in global economic losses resulting from weather-related events with associated insured losses over the period 1980 to 2019. As shown, the protection gap, that is the difference between insured and total losses, has widened over time in absolute terms, but has reduced in proportion. This highlights the ongoing under-insurance of society even with growth in penetration. It also points to the still large insurance opportunity to fill the gap and build resilience.

Climate change and rising losses: work in progress

With global temperatures warming, we expect that hazard intensification will likely play a greater role in increasing the economic losses resulting from weather-related events in the decades to come. After remaining relatively stable for approximately 12,000 years – corresponding to the full duration of human civilization – the climate is changing, with temperatures now 1.0°C above pre-industrial times. Most physical processes that define our climate and its extremes depend directly or indirectly on the temperature of the atmosphere and the oceans. Hence, any change in global temperatures and their extremes, whether from greenhouse-gas emissions or due to natural variability, will alter the risks that humans and the world are exposed to.

In parts of the world, some secondary-peril events such as drought, wildfire and floods have and will continue to become more extreme, due to ever-drier weather conditions, increases in precipitation and rising sea levels. For some secondary perils like heatwaves, observations, physical theories and numerical models all converge to show an increase in both frequency and intensity in most parts of the world. The effects are also feeding through to higher insurance losses on account of property damage, crop shortfalls, business interruption claims and others.

Figure 7
Global economic versus insured losses resulting from weather-related catastrophes, 1980–2019, (USD billion, 2019 prices)

Source: Swiss Re Institute

Figure 2: Insurance gap – Source: Swiss Re, 2020.
Weather disaster losses rise as economies grow and climate changes.

**Economic growth and urbanisation: key exposure drivers**

Both the number of and economic losses from storms, floods and other extreme weather-related events have risen significantly over recent decades (see Figure 2). The trend of rising losses has been more evident since the mid-1990s, with improved data from more comprehensive and inclusive reporting of events likely contributing. Conversely, the less noticeable gains in losses in the 1980s can in part be explained by the lesser availability of data.

There are many underlying drivers to the rising losses resulting from weather-related events. The main factor is growing exposures as the world’s population continues to rise and, with economic growth, urbanisation and asset values increase. Over the last 60 years, the world’s population has grown by approximately 2.5-times, and global real gross domestic product (GDP) by more than sevenfold.

Urban areas comprise the highest concentration of people and assets. In the 1950s, around 30% of the global population lived in urban areas. Today more than 50% does, and this is forecast to rise to near 70% by 2050.

Three main components determine the impact of weather-related risks: hazard or type of peril (hurricane, flood etc); exposure, which refers to the populations and assets that lie in the path of weather-related hazards; and vulnerability (the susceptibility of the exposed elements to the hazards). Figure 3 outlines the complex interplay between the physical and socio-economic components of the weather-related risk equation. Weather-related hazard occurrence is dependent on climate conditions, changes in which are largely due to natural variability. Of late there has been an increase in the occurrence of weather-related events.

Various factors influence the scale of losses inflicted by weather events. Since 1980, exposure accumulation due to economic growth and urbanisation has been the main driver of the increase in associated losses. Normalised losses accounting for GDP growth and inflation further confirm the trend of rising losses resulting from weather-related events. We expect that climate change effects will play an increasing role in the next decades. However, with a lack of granular data on the many contributing components, including socio-economic factors, attribution modelling remains work in progress.

**Figure 2**
Number of weather-related events and associated economic losses, 1970-2019 (USD billion, 2019 prices)

**Figure 3:** Weather-related events and losses – Source: Swiss Re, 2020.
Catastrophe bonds and ILS cumulative issuance by year

Cumulative cat bond issuance and number of deals by year – From the Artemis Deal Directory

Source: www.Artemis.bm Deal Directory
Temperature Indexed Swap (TIS)

Protection buyer and protection seller exchange cash flows at $t + h$ (maturity). On date $t$ (negotiation date):

\[
\mathbb{E}_t(M_{t,t+h}T_{t+h}) = \mathbb{E}_t(M_{t,t+h}T_{t,h}^S).
\]

**Figure 4: TIS**
**Temperature Indexed Bond (TIB)**

Debt instrument whose payoff at maturity \((t + h)\) is indexed to a given measure of temperature (or carbon concentration). Specifically:

\[
1 + \chi [T_{t+h} - \mathbb{E}_t(T_{t+h})],
\]

where \(\chi\) is a “leverage factor”.

Note: the payoff expectation is equal to 1.

---

**Temperature Options**

Nonlinear payoffs.

<table>
<thead>
<tr>
<th>Option type</th>
<th>Price (notation)</th>
<th>Payoff (settled on maturity date (t + h))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital</td>
<td>(D_{igt,h}(T_K))</td>
<td>(1{T_{t+h}&gt;T_K})</td>
</tr>
<tr>
<td>Call</td>
<td>(C_{all,t,h}(T_K))</td>
<td>((T_{t+h} - T_K)^+ = 1{T_{t+h}&gt;T_K}(T_{t+h} - T_K))</td>
</tr>
<tr>
<td>Put</td>
<td>(P_{ut,t,h}(T_K))</td>
<td>((T_{t+h} - T_K)^- = 1{T_{t+h}&lt;T_K}(T_K - T_{t+h}))</td>
</tr>
</tbody>
</table>
(a) – Risk-Adjusted Temperature in 2100

Swap Price minus Expected $T_{\text{AT},2100}$, $\mu_N$, calibrated (~30) vs $\mu_D$.

(b) – Social Cost of Carbon

Social Cost of Carbon (SCC) in $/GTC$, $\mu_N$, calibrated (~30) vs $\mu_D$.

(c) – Long-term Real Interest Rate (50 years)

Real Rate (in percent), $\mu_N$, calibrated (~30) vs $\mu_D$.