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ABSTRACT

There is a rapidly advancing literature on the macroeconomics of climate change. This review focuses on developments in the construction and solution of structural integrated assessment models (IAMs), highlighting the marriage of state-of-the-art natural science with general equilibrium theory. We discuss challenges in solving dynamic stochastic IAMs with sharp nonlinearities, multiple regions, and multiple sources of risk. Key innovations in deep learning and other machine learning approaches overcome many computational challenges and enhance the accuracy and relevance of policy findings. We conclude with an overview of recent applications of IAMs and key policy insights.

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1 Introduction

Since the Industrial Revolution, the Earth has warmed by roughly 1.1°C due to the anthropogenic emission of greenhouse gases, most notably carbon dioxide (CO_2), from the burning of fossil fuels. The consequences of anthropogenic climate change – manifested in the higher frequency of wildfires, droughts, floods, and hurricanes, among other events – are already being felt in many parts of the world. Numerous reduced-form empirical studies have documented the clear economic impacts of these changes. Moreover, the vast availability of carbon-based energy sources such as oil, gas, and coal with relatively low exploitation costs means that, without policy action, continued CO_2 emissions are likely to further endanger our planet and lower social welfare. The effects of climate change might indeed be severe, as natural science predicts that the frequency and intensity of extreme events increase with rising temperatures (Masson-Delmotte et al., 2021, Davariashtiyani et al., 2023, and Russo and Domeisen, 2023).[1]

Thus, there is a broad consensus that substantial greenhouse gas emission reductions are required. The natural science community has called for limiting the rise of global mean surface temperature to 1.5°C, the goal of the Paris 2015 Agreement. Many governments and institutions are aggressively trying to lower greenhouse gas emissions, including the European Commission and the European Central Bank, as well as the United States, with its Bipartisan Infrastructure Law and Inflation Reduction Act. However, countries' pledges to reduce emissions are currently woefully short of limiting global warming to the Paris target, and there is substantial uncertainty about the future trajectory of emission reductions.

Macroeconomics can provide instruments for studying how to reach the goals for greenhouse gas emission reduction in ways that are efficient and politically feasible. More specifically, the macroeconomics of climate change can be defined as an interdisciplinary domain that examines the economic determinants and consequences of climate change through a macroeconomic lens (Stern, 2008). This effort includes understanding how climate change impacts economic growth, development, technological change, and globalization, as well as exploring the economic underpinnings of climate-related policies and unearthing unintended consequences.

This review summarizes the state of the art in the macroeconomics of climate change from a structural perspective, in which we have models with agents optimizing and endogenous

[1] The sixth report of the Intergovernmental Panel on Climate Change (IPCC) can be found at: https://www.ipcc.ch/assessment-report/ar6/.

choices. In particular, we describe how to build and solve integrated assessment models (IAMs), which were first pioneered by Nordhaus (1979) and have long served as a workhorse tool for the study of the macroeconomics of climate change.

The structural IAMs we study are explicit about the preferences, technology, and information sets of the economy's agents; these agents respond optimally to prices and taxes, and markets clear. These features make IAMs attractive because they quantify the economic effects of climate change, including:

1. Capturing the nonlinear, dynamic, endogenous, and stochastic nature of economic and climate systems.
2. Building middle- and long-run forecasts that incorporate the endogenous reactions of agents to changes in economic policy and climate.
3. Gauging the costs and benefits of different policies.

More specifically, by allowing the construction of a rich set of counterfactuals, IAMs provide a foundation for informed decision-making. Hence, IAMs are an essential tool for policymakers and researchers, blending theoretical rigor with practical relevance.

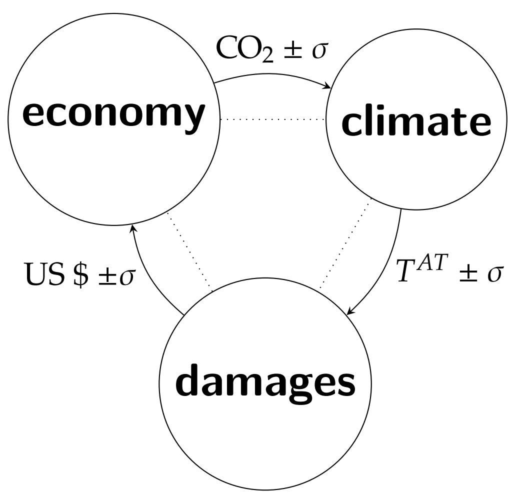

Figure 1: Stylized representation of an IAM.

Figure 1 shows how an IAM model of climate change can be represented by three building blocks, each of which may entail stochastic elements: i) an economic module, ii) a climate module, and iii) a damage module. This stylized diagram abstracts from many details but provides a high-level overview of the key connections between the building blocks.

The economic module generates greenhouse gases such as CO_2, which might be stochastic in projections (hence the σ to denote the degree of uncertainty). A common model is a dynamic stochastic general equilibrium (DSGE) model that produces output using (exhaustible) fossil fuels emitting CO_2 and other greenhouse gases into the atmosphere (Dasgupta and Heal, 1974). The DSGE models are designed to incorporate dynamics, uncertainty, and endogenous growth.

The atmospheric concentrations of CO_2 and other greenhouse gases influence the climate, with the global mean surface temperature T^{AT} as the primary variable of interest. For the handshake between those two building blocks, economists typically rely on simplified climate models —-the so-called climate emulators-— that provide a realistic quantitative link between CO_2 emissions and global warming at low computational costs.[2]

The temperatures are then fed into a damage module, which at its core is usually a "damage function." Damage functions are functional relationships describing how global temperature increases or other climate change indicators lead to economic costs. Essentially, they translate the physical effects of climate change – such as sea-level rise, increased frequency of extreme weather events, and changes in agricultural productivity – into monetary values. As with the other blocks, the damage function can be stochastic.

IAMs are inherently quantitative, designed to estimate, for instance, the amount of global and local warming of the planet (measured in °Celsius) under different scenarios, the social cost of carbon (SCC), optimal carbon taxes, and schemes for Pareto improvements, among others.[3] They stem from a tradition in macroeconomic research that emphasizes empirically grounded theory, often utilizing general equilibrium modeling that integrates microeconomic foundations with an aggregate perspective (Hassler et al., 2016). This approach enables the examination of policy's effect on welfare and the comparison of different policy scenarios.

However, structural IAMs are highly computationally intensive because they are dynamic, stochastic, nonlinear, nonstationary, and forward-looking. Furthermore, they often exhibit significant heterogeneity across time and space. Finally, researchers have to explore a wide range of scenarios and delve into the underlying mechanisms of these models to obtain analytical

[2]The key functionality of any climate emulator is to translate anthropogenic emissions, as computed by the economic model, into a global mean temperature change. In most emulators, the task is typically split into two parts: a "carbon cycle," which translates anthropogenic emissions in the wake of human economic activity into changes in the atmospheric CO_2 concentration, and a temperature model, which translates changes in atmospheric CO_2 concentrations into (possibly stochastic) global mean temperature changes. See Nordhaus (2017).

[3]The SCC represents the marginal cost of carbon emissions, defined as the aggregate of all future damages caused by an incremental increase in CO_2 emissions, discounted at the market interest rate.

insights into the economic implications of climate change.

Accordingly, economists have deployed powerful computational tools for resolving and analyzing their nonlinear and dynamic attributes. For example, working with DSGE models in the climate space often entails the application of state-of-the-art global solution techniques and high-speed computing hardware.[4] Solving such models computationally in a way that is accurate and fast is especially important, as closed-form solutions to IAMs are rarely available. Applying such a computational approach is consistent with practices in the natural sciences, where numerical solutions are the norm.

Nevertheless, the implications of IAMs often greatly depend on assumptions for parameters and functional forms. Pindyck (2013) expresses concerns about the broad use of IAMs and criticizes them as having shortcomings that render them nearly ineffective for policy analysis. As we will discuss in this article, this critique is mitigated by the considerable progress made in the last decade across the foundational elements of IAMs. The introduction of powerful computational techniques (e.g., from machine learning) for model solutions, richer datasets for better empirical parameterizations, and enhanced integration between natural science and economic models have led to significant evolution in the IAM landscape. This progress has rendered IAMs a valuable tool for informed and robust decision-making in climate change mitigation (Weyant, 2024).

Because of space limitations, our review focuses on developments in the macroeconomics literature on climate change over the last decade. Unlike previous excellent reviews such as those by Hassler et al. (2016), Hassler and Krusell (2018), Desmet and Rossi-Hansberg (2024), and Hassler et al. (2024a), we home in on recent advances in the construction and numerical solution of both globally and spatially-resolved, richly formulated dynamic IAMs, emphasizing accuracy and computational efficiency.

For the same reason, we also skip the review of more reduced-form analyses of the link between the aggregate economy and climate change. The interested reader can consult Burke et al. (2015), Carleton et al. (2022), and Tol (2023). Suffice it to say here that structural and reduced-form approaches can complement each other for many purposes, building on their comparative strengths and weaknesses.

[4] We adopt the terminology from Brumm and Scheidegger (2017), where we refer to a "global solution" as a solution computed utilizing equilibrium conditions at numerous points within the state space of a dynamic model, as opposed to a "local solution," which relies on a local approximation around a model's steady state.

The remainder of this review is organized as follows. Section 2 presents a prototypical dynamic IAM to illustrate how the various components of natural science and macroeconomics are combined. Section 3 reviews recent advances in natural science inputs available to IAM modelers at low computational costs. Section 4 briefly summarizes the literature on how damage functions can be modeled. Section 5 discusses advancements in computational methods for solving IAMs. Section 6 explores some recent applications of IAMs for studying particular macroeconomic questions. Section 7 concludes.

2 A Prototypical Dynamic IAM

To introduce how the various components of an IAM work, we rely on the seminal *Dynamic Integrated Model of Climate and the Economy* DICE-2023 model (Barrage and Nordhaus, 2024). While relatively simple, this model incorporates all the building blocks and terminology commonly found in dynamic IAMs and, therefore, is perfect to illustrate the ideas we want to highlight.

The economy is the key non-climate part of this prototypical dynamic IAM, and it consists of a single, infinitely lived, representative consumer and a single firm. The equilibrium allocation can be described as the solution to a planner's problem. See Golosov et al. (2014) for more details, and Kotlikoff et al. (2021a) and Kotlikoff et al. (2023) for a critique of this approach.

The planner maximizes a time-separable utility function over per capita consumption $\left(\frac{C_t}{L_t}\right)_{t=0}^{\infty}$, where C_t is total consumption, L_t population, and A_t total factor productivity (TFP). Each period's preferences are represented by a CRRA utility of consumption with risk aversion ϕ. This parameter reflects the degree of substitutability between consumption across different years or generations. The time discount factor is $0 < \beta < 1$.

The optimal value, V_0, is given by:

$$V_0 = \max_{\{C_t,\mu_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \frac{\left(\frac{C_t}{L_t}\right)^{1-\phi} - 1}{1-\phi} L_t \tag{1}$$

$$\text{s.t.} \quad C_t + K_{t+1} = (1 - \Theta(\mu_t) - \Omega(T_t^{\mathrm{AT}}))K_t^{\alpha} (A_t L_t)^{1-\alpha} + (1-\delta)K_t \tag{2}$$

$$\text{A tractable climate model} \tag{3}$$

given K_0 and the boundary conditions $0 \le K_{t+1}$ and $0 \le \mu_t \le 1$.

Gross output $K_t^{\alpha}\left(A_t L_t\right)^{1-\alpha}$ is produced using a Cobb-Douglas technology with capital, K_t, and labor, L_t. Mitigation, μ_t, is costly and decreases available output for consumption and investment at a rate $\Theta(\mu_t)$. Higher temperatures (increases in T^{AT}) also decrease available output with a functional form given by the damage function $\Omega(T_t^{\mathrm{AT}})$.[5] The online appendix of Barrage and Nordhaus (2024) provides a specification of all the equations, including exogenous variables and damages.

Greenhouse gas emissions (which we proxy for with CO_2 emissions) are denoted by E_t, given by $E_t = E_t^{\mathrm{Land}} + (1-\mu_t)\gamma_t K_t^{\alpha}\left(A_t L_t\right)^{1-\alpha}$. They consist of non-industrial emissions, E_t^{Land}, and industrial emissions, which are modeled as a fraction γ_t of gross output minus mitigation $1-\mu_t$. Emissions are linked to a numerically tractable climate model via equations (3), the details of which will be provided in Section 3.

We can find two different solutions to the social planner's problem. First, is the solution when the planner ignores the possibility that higher mitigation (increasing μ_t) leads to lower damages from a temperature increase. In this so-called business-as-usual (BAU) scenario, the planner only chooses consumption in equation (2) and mitigation is set to zero. Second, the social planner solves the problem by choosing consumption and mitigation optimally.

In both cases, the SCC is the present discounted value of the marginal cost of atmospheric carbon in terms of the numeraire good. Following the literature (e.g., Traeger, 2014, and Cai and Lontzek, 2019), we can write the SCC as the planner's marginal rate of substitution between the atmospheric carbon concentration and the capital stock:

$$SCC_t = -\frac{\partial V_t / \partial M_{\mathrm{AT},t}}{\partial V_t / \partial K_t}.$$

The optimal carbon tax (CT_t) is the tax that equates the private and the social cost of carbon. Nordhaus (2017), among others, rewrites this optimal carbon tax as a function of μ_t. More concretely, the social planner chooses mitigation μ_t, which is equivalent to choosing the carbon tax in units [USD/tC]:

$$CT_t = \frac{\theta_{1,t}\theta_2 \mu_t^{\theta_2 - 1}}{\gamma_t},$$

where $\theta_{1,t}$ and $\theta_{2,t}$ are the parameters controlling the abatement cost $\Theta(\mu_t)$. By definition, the

[5] We are introducing damages in output, but one could also consider damages inside the utility function (1).

SCC equals the optimal carbon tax if $\mu_t < 1$.[6]

While this model is relatively simple and deterministic, it already consists of many state variables (K_t plus all the climate-related variables), is nonstationary, and exhibits nonlinearities, such as those introduced by a convex damage function.[7] This explains why dynamic IAMs are inherently difficult to solve. Tackling complex IAMs, such as those including multiple regions and multiple sources of risk, is correspondingly much more challenging.

3 Advances in Tractable Natural Science Inputs to IAMs

Given the interdisciplinary nature of IAMs, it is valuable for economists to understand the basic building blocks of climate science, even if only to become familiar with the terminology. The economics of climate change begins with the greenhouse effect, which occurs when CO_2 and other greenhouse gases in the Earth's atmosphere trap heat. Typically, the Earth absorbs energy from the Sun and releases it back into space as infrared radiation. However, CO_2 absorbs some of this infrared radiation, preventing it from escaping into space. Instead, the heat is re-emitted in all directions, including back toward the Earth's surface, causing the planet to warm. As CO_2 levels rise, more heat is trapped, contributing to global warming.

Once emitted, CO_2 remains in the atmosphere for centuries. In comparison, the climate system operates across a wide range of timescales, from seconds to millennia (Joos et al., 2013). Thus, precise yet computationally tractable representations of global —- and, in spatial IAMs, local -— climate dynamics via emulators in IAMs are essential for formulating effective policy recommendations (Dietz et al., 2021).

The literature on climate-change economics features a proliferation of different emulators. The most popular ones are found in DICE (Nordhaus, 2017), FUND (Tol, 1997), PAGE (Hope, 2013), and Golosov et al. (2014). Unfortunately, as Calel and Stainforth (2017) point out, *"In failing to maintain clear links to the physical science literature, the climate components of these models have become opaque to the scientific community."* Moreover, until recently, economics had little consensus on what constitutes a *"good"* climate model, particularly with respect to the data to

[6]The conversion factor between carbon (C) and carbon dioxide (CO_2) is based on their molecular weights: carbon has a molecular weight of 12 g/mol, while CO_2 has a molecular weight of 44 g/mol. Thus, one ton of carbon corresponds to approximately 3.67 tons of CO_2.

[7]Under certain assumptions, the climate-related state variables can be reduced to a single variable. However, this reduction comes at the cost of reduced generality and accuracy (see Section 3.2 for more details).

which the model should be calibrated.[8]

Dietz et al. (2021) demonstrate that most economic models of climate change produce climate dynamics inconsistent with current climate-science models. Specifically, they found that "*...(i) the delay between CO_2 emissions and warming is much too long and (ii) positive carbon cycle feedbacks are mostly absent. These inconsistencies lead to biased economic policy advice. Controlling for how the economy is represented, different climate models result in significantly different optimal CO_2 emissions. A long delay between emissions and warming leads to optimal carbon prices that are too low and attaches too much importance to the discount rate.*" Furthermore, they find that "*...omitting positive carbon cycle feedbacks leads to optimal carbon prices that are too low*" and call for integrating state-of-the-art climate science into our economic models.

Therefore, we will review a climate emulator designed to replicate accurately the global climate system with five state variables at relatively low computational costs. Then, we will examine a highly efficient emulator based solely on cumulative emissions (one single state variable), which can, under certain conditions, provide large computational gains when embedded into an IAM. Finally, since understanding regional climate damages requires knowledge of regional temperatures, we discuss methods for deriving local temperatures from global ones.

3.1 Modelling the Global Climate with CDICE

Folini et al. (2024) recently bridged the gap between the natural sciences and economics by proposing a generic and transparent calibration and evaluation strategy for climate emulators based on easily accessible state-of-the-art benchmark data from climate sciences. As a concrete example, the authors present a carefully calibrated DICE-2016 (Nordhaus, 2017) climate emulator, which they call CDICE, with five state variables. Despite its relative simplicity, the DICE model includes components that effectively mimic Earth system models in a straightforward, clear, and relatively accurate manner.

We outline this procedure adhering to the notation used by Folini et al. (2024). At its core, CDICE translates carbon emissions from the economy into atmospheric CO_2 concentrations and, subsequently, into a global mean temperature change, which then feeds back into the part

[8] Barrage and Nordhaus (2024) address the critique by Dietz et al. (2021) regarding the performance of the DICE-2016 climate emulator by implementing the fix suggested by the latter and introducing the DFAIR module, a version of the FAIR (Finite Amplitude Impulse-Response) model specifically adapted for DICE. For an open-source implementation of FAIR, see `https://github.com/OMS-NetZero/FAIR/tree/master` (Millar et al., 2017).

of the model that represents the economic side of the IAM. The carbon cycle is a linear three-box model, where the three carbon reservoirs represent the atmosphere (AT), the upper ocean (UO), and the lower ocean (LO), with the respective carbon masses $M = (M^{\mathrm{AT}}, M^{\mathrm{UO}}, M^{\mathrm{LO}})$. Carbon can be exchanged between the atmosphere and upper ocean and between the upper and lower ocean, but not directly between the atmosphere and lower ocean. The global mean temperature is modeled via a system of two ordinary differential equations that couple two heat reservoirs, the atmosphere plus the upper ocean and the lower ocean, $T = (T^{\mathrm{AT}}, T^{\mathrm{LO}})$.

The carbon cycle model (Keeling, 1973) is

$$M_{t+1} = (I + \Delta_t \cdot B) \cdot M_t + \Delta_t \cdot E_t,$$

with I being the identity matrix, Δ_t the time step in years, and $M_t = (M_t^{\mathrm{AT}}, M_t^{\mathrm{UO}}, M_t^{\mathrm{LO}})$ the carbon mass at time t in the three reservoirs. The carbon emissions per year to the atmosphere and the ocean are given by E_t.

The mass transfer among reservoirs is described by a time-constant matrix:

$$B = \begin{pmatrix} b_{11} & b_{21} & b_{31} \\ b_{12} & b_{22} & b_{32} \\ b_{13} & b_{23} & b_{33} \end{pmatrix},$$

which has units "mass fraction per time step." Assuming that mass conservation holds, that is, $\sum_i b_{ji} = 0$ for $j = 1, 2, 3$, and that there is no direct mass transfer between AT and LO (implying that $b_{13} = b_{31} = 0$), leaves four free parameters in B that are used to calibrate the carbon cycle. In DICE, these parameters are chosen as the transfer coefficients from AT to UO (b_{12}) and from UO to LO (b_{23}), as well as the equilibrium carbon mass ratios at pre-industrial times between the reservoirs, $r_1 = M_{\mathrm{EQ}}^{\mathrm{AT}}/M_{\mathrm{EQ}}^{\mathrm{UO}}$ and $r_2 = M_{\mathrm{EQ}}^{\mathrm{UO}}/M_{\mathrm{EQ}}^{\mathrm{LO}}$. The remaining matrix entries b_{ij} are then given by $b_{11} = -b_{12}$; $b_{21} = b_{12} \cdot r_1$; $b_{22} = -b_{21} - b_{23}$; $b_{32} = b_{23} \cdot r_2$; $b_{33} = -b_{32}$.

We now present some details of the calibration since it is useful for economists to get a sense of a reasonable range of parameter values. Table 1 provides parameter values for B.

Parameter	b_{12}	b_{23}	M_{EQ}
Value	0.054	0.0082	(607, 489, 1281)

Table 1: Values of parameters in the carbon cycle of CDICE (multi-model mean calibration).

The two-layer energy balance model in CDICE follows Geoffroy et al. (2013):

$$T_{t+1}^{\text{AT}} = T_t^{\text{AT}} + \Delta_t \cdot c_1 \left(F_t - \lambda T_t^{\text{AT}} - c_3 \left(T_t^{\text{AT}} - T_t^{\text{OC}}\right)\right), \tag{4}$$

$$T_{t+1}^{\text{OC}} = T_t^{\text{OC}} + \Delta_t \cdot c_4 \left(T_t^{\text{AT}} - T_t^{\text{OC}}\right). \tag{5}$$

T_t^{AT} and T_t^{OC} denote the temperature change with respect to pre-industrial times of the upper layer (atmosphere and upper ocean) and the lower layer (deep ocean), respectively, at time step t. The free parameters c_1, c_3, c_4, and λ in equations (4) and (5) have to be calibrated. Additionally, F_t denotes the total radiative forcing from CO_2, $F_t^{CO_2}$, and other exogenous factors, F_t^{EX}, such as greenhouse gases other than CO_2 and aerosols:

$$F_t = F_{2\text{XCO}_2} \frac{\log\left(M_t^{\text{AT}}/M_{\text{EQ}}^{\text{AT}}\right)}{\log(2)} + F_t^{\text{EX}}.$$

In CDICE and Nordhaus (2017), F_t^{EX} is assumed to change linearly with time from 0.5 in 2015 to 1.0 in 2100. The initial values for the carbon and temperature reservoirs used in CDICE for 2015 are $M_{\text{INI}} = (851, 628, 1323)$ and $T_{\text{INI}} = (1.10, 0.27)$ in their multi-model mean calibration. Table 2 summarizes the remaining parameter values for CDICE.[9]

Model Parameter	c_1	c_3	c_4	ECS	F_{2XCO_2}	λ
Parameter Value	0.137	0.73	0.00689	3.25	3.45	1.06

Table 2: Values of the parameters of the temperature equations for CDICE (multi-model mean calibration).

[9]The multi-model mean, though debated, is a commonly used benchmark in climate science (Beusch et al., 2020). The CDICE emulator can be recalibrated for extreme climate scenarios, to which the solutions of IAMs are sensitive, as discussed in Folini et al. (2024).

3.2 Cumulative Carbon Emissions and Temperature

Climate science has established a near-linear relationship between cumulative CO_2 emissions and the resulting global warming:

$$T_t^{AT} \approx \sigma_{CCR} \sum_{s=0}^{t} E_s, \tag{6}$$

where T_t^{AT} denotes the change in global mean surface temperature, due to cumulative global emissions E_s, and σ_{CCR} is the constant of proportionality, referred to as the carbon-climate response (CCR) or the transient climate response to cumulative carbon emissions (TCRE) (Matthews et al., 2009). Recent IPCC reports suggest that σ_{CCR} likely ranges between 1.0°C and 2.3°C per 1,000 GtC (Costa et al., 2021, Chapter 5.5.1.4), implying a temperature rise of 0.27°C to 0.63°C per 1,000 $GtCO_2$ emitted.

From a computational perspective, equation (6) is attractive because it involves a single state variable (in contrast to the five state variables from the model outlined in Section 3.1), making it particularly popular in analytical IAMs where closed-form solutions can be derived (Dietz and Venmans, 2019), or in contexts where economizing on state variables is necessary.

However, this straightforward climate emulator should be used with caution in dynamic IAMs. First, one must quantify the uncertainty surrounding σ_{CCR}. Second, the quasi-linear relationship between temperature and CO_2 is derived from past observations and future simulations using models that are well-behaved and lack significant endogenous nonlinearities, such as tipping points (Lenton et al., 2008). If such nonlinearities are present, then this model may be inadequate for projecting global average temperature, reflecting limitations in the underlying large-scale climate models—specifically Atmosphere-Ocean General Circulation Models (AOGCMs) and Earth System Models (ESMs). Third, while the CCR model may be suitable for scenarios involving CO_2 emissions, it does not adequately (i) represent non-CO_2 greenhouse gases, such as methane, that constitute a significant part of the emissions problem or (ii) evaluate the possibility of negative emissions of CO_2 (Kirschke et al., 2013).

3.3 Local Climate Projections

If one intends to study IAMs with spatial resolution (e.g., Nordhaus and Yang, 1996, Krusell and Smith, 2022, Cruz and Rossi-Hansberg, 2024, Desmet and Rossi-Hansberg, 2024, and Kotlikoff et al., 2024, among others), knowledge of regional damages – and, therefore, regional temperatures – is typically required.

The regional temperatures T_t^z at a location z can be accurately inferred from global temperatures without the need to compute a local climate model by using a popular and computationally efficient technique from climate science known as "pattern scaling," also referred to as "statistical downscaling" (see Tebaldi and Arblaster, 2014, Kravitz et al., 2017, Lynch et al., 2017, Mathison et al., 2024, and references therein). Pattern scaling, first introduced by Santer et al. (1990), is a statistical method that uses large-scale Earth system models to relate the global average temperature, T_t^A, to local temperatures T_t^z at a specific location z, with resolutions as fine as $1°$ longitude $\times$ $1°$ latitude, via regression analysis.

Formally, pattern-scaling methods provide functional relations such as:

$$T_t^z = f\left(T_t^{\mathrm{A}}\right) + \eta_t^z,$$

where the local temperature T_t^z at grid point z and time t is defined as a response to the global mean temperature T_t^A, indicated by the function $f(\cdot)$, and a stochastic local residual temperature variability term $\eta_{z,t}$ (Beusch et al., 2020).

Thus, once the global temperature is determined, e.g., via equation (4), the local temperature can be inferred and then applied in a spatially resolved IAM.[10]

4 Modeling Economic Damages

Estimating the costs of greenhouse gas emissions is crucial for informed policymaking (Stern, 2007, Hänsel et al., 2020, Burke et al., 2023, and Bilal and Känzig, 2024). In the context of dynamic IAMs, these costs are computed using damage functions, which typically quantify

[10]Various pattern-scaling repositories are publicly available, such as the one by Lynch et al. (2017), which can be found at https://github.com/JGCRI/CMIP5_patterns; the one by Hernanz et al. (2023), with open source code that can be accessed at https://github.com/ahernanzl/pyClim-SDM; or Beusch et al. (2020), who provide codes at https://github.com/MESMER-group/mesmer-openscmrunner.

economic losses due to climate change as a function of global mean temperature rise.

A substantial and growing body of literature explores the construction and estimation of parametric and nonparametric damage functions, with recent notable contributions by Burke et al. (2015), Rode et al. (2021), Carleton et al. (2022), and Cruz and Rossi-Hansberg (2024). There are two main approaches to the construction of damage functions: the bottom-up method, which identifies various types of damages, assigns monetary values (usually using market prices), and aggregates them, and the top-down method, which relates macroeconomic aggregates to observed climate changes over time or spatial climate differences. For two summaries, see Desmet and Rossi-Hansberg (2024) and Hassler et al. (2024b).

In most IAMs, including our prototypical IAM, damage functions are incorporated into the economic output equation to account for the reduction in available output at higher temperatures, as we showed in equation (2). The usual starting point is the assumption that net output is gross output reduced by damages and mitigation costs, e.g., $Y_t^{\text{net}} = (1 - \Omega(T_t^{\text{AT}}) - \Theta(\mu_t))Y_t$. In this specification, Y_t^{net} is output net of damages and abatement (μ_t), Y_t is gross output, and T_t^{AT} is again the atmospheric temperature, all at time t. In the DICE-2023 model (Barrage and Nordhaus, 2024) and much other research, the functional form used to model damages is assumed to be quadratic:

$$\Omega(T_t^{\text{AT}}) = \psi_1 T_t^{\text{AT}} + \psi_2 (T_t^{\text{AT}})^2, \tag{7}$$

where $\psi_1 = 0.0$ and $\psi_2 = 0.003467$.[11]

While the mechanics of adding damages are similar across different studies, the functional form of the damages remains debated. For instance, Hänsel et al. (2020) criticize the DICE damage function, advocating specifications that produce larger damages for a given rise in temperature. Weitzman (2012) argues for a damage function with a polynomial of order 6.8 to account for severe outcomes. In contrast, Cai and Lontzek (2019) use the standard deterministic damage function from DICE but add a stochastic tipping point component. Their study's multi-layer tipping point risk is modeled via a compound Markov chain and resembles a representative tipping point process with stochastic occurrence, duration, and magnitude of impact.

Since global warming and its associated damages are far from uniform (Carleton et al., 2022),

[11] The file https://yale.app.box.com/s/whlqcr7gtzdm4nxnrfhvap2hlzebuvvm/file/1361579245945 summarizes the parameterization of DICE-2023.

spatially resolved IAMs incorporate local damage functions $\Omega^z(T_t^z)$ that are functions of the local temperature. These are important for a variety of climate-related policy questions, such as the effect on insurance markets (Moore, 2024). A popular way to model local TFP damages put forward by Krusell and Smith (2022) and adopted in spirit, for instance, by Hassler et al. (2023) and Kotlikoff et al. (2024), is to use functional forms that are U-shaped in local temperature T_t^z. These functions peak around 11.6 °C, the empirical maximum temperature for TFP, and have parameters that are chosen such that, when aggregated, the functions can replicate aggregate global damage functions such as the one presented in equation (7). For more details, see Desmet and Rossi-Hansberg (2024).

5 Computational Advances

Solving IAMs and performing uncertainty quantification with them is a numerically daunting task, as they entail stochastic elements in i) the economic block of the model (e.g., to deal with stochastic growth and long-run risks, such as in Jensen and Traeger, 2014, Cai and Lontzek, 2019, and van den Bremer and van der Ploeg, 2021), ii) the climate block (e.g., to model the equilibrium climate sensitivity, such as in Roe and Baker, 2007, Zaliapin and Ghil, 2010, Kelly and Tan, 2015, and Hwang et al., 2017, and stochastic tipping points, such as in Lenton et al., 2008, and Cai and Lontzek, 2019); and iii) more generally, in terms of model uncertainty (e.g., Barnett et al., 2020, and Zhao et al., 2023). Furthermore, IAMs can be highly nonlinear, are inherently nonstationary, and may contain much heterogeneity across different agents as well as regions (Desmet and Rossi-Hansberg, 2024, and Kotlikoff et al., 2024).

Tackling such models calls for powerful global solution methods, but those methods suffer from an acute curse of dimensionality.[12] Consequently, IAM modelers have traditionally hesitated to fully embrace the complexity demanded by uncertainty quantification of richly formulated IAMs, thus sidestepping the computational intricacies involved.

The traditional approach to uncertainty quantification in IAMs is to assume distributions for a key set of parameters and run Monte Carlo simulations to build insight into changes in outcome variables, such as the SCC, global mean surface temperature, and consumption

[12] Think about standard grid-based algorithms: starting with a one-dimensional discretization scheme that employs N grid points, a straightforward extension to d dimensions leads to N^d points. Thus, the total number of points grows exponentially in the dimension.

(Nordhaus and Popp, 1997, Pizer, 1999, Anderson et al., 2014, Butler et al., 2014, Miftakhova, 2021). The basic strategy of perturbing an input variable to see the effect on output variables is known as a sensitivity analysis and when performed simultaneously using distributions of multiple parameters, a global sensitivity analysis (Saltelli et al., 2007). A Monte Carlo approach has also been used across multiple models to examine differences in the sensitivity of outcomes across model structures (Gillingham et al., 2018).

However, such an approach does not allow agents, and in particular, the social planner, to optimize under uncertainty. Usually, the analysis is performed in a non-stochastic setting (and perhaps a local perturbation of solutions to stochastic models). For example, instead of letting the social planner explicitly account for the uncertainty in optimizing the choice of carbon price, the approach calculates the optimal carbon price in a deterministic setting at different values of the input parameters drawn from a distribution. While computationally tractable and transparent, this strategy is not a complete uncertainty analysis. Fortunately, substantial progress has been made over the past decade by adapting new computational tools to the solution of IAMs, some of which we will now briefly review.[13]

Cai and Lontzek (2019) propose a massively parallelized dynamic programming algorithm that leverages Chebyshev polynomials as function approximations to solve for the first time stochastic IAMs with tipping elements, long-run risk, and economic risk at the expense of about $O(100k)$ CPUh per simulation. Thus, the authors can study how uncertainty affects, for instance, the stochastic distribution of SCC over time. While this work provides a substantial breakthrough, their approach is still a significant roadblock for various tasks such as parametric uncertainty quantification, which requires thousands, if not tens of thousands, of individual model solutions to obtain convergent statistics (Harenberg et al., 2019). Hence, such a task is out of reach with the mentioned solution technique.

To alleviate these limitations, the literature has begun to embrace tools from the machine learning field. For instance, Kotlikoff et al. (2021b) use Gaussian process regression, a form of supervised machine learning that can approximate high-dimensional, nonlinear policy functions with relatively few observations on arbitrary geometries (Scheidegger and Bilionis, 2019). This method is combined with so-called "self-justified equilibria" (Kubler and Scheidegger, 2019), a dimension-reduction technique based on "active subspaces" (Constantine et al., 2014), to tackle

[13] There is work on finding analytical simplifications on IAMs, such as Golosov et al. (2014), Rezai and Van der Ploeg (2016), Dietz and Venmans (2019), and Traeger (2021).

a stochastic overlapping generations (OLG) model with economic and climate risks. While this solution technique allows studying Pareto-improving carbon-risk taxation on a laptop in a few hours, it encounters troubles in the presence of strong nonlinearities.

Another recent and promising avenue to tackle large-scale dynamic stochastic IAMs with a lot of nonlinearity has been proposed by Friedl et al. (2023), who suggested applying "deep equilibrium nets" (DEQN) (Azinovic et al., 2022). Their approach consists of two distinct parts. First, they enhance a generic DEQN such that it can be used to solve stochastic IAMs globally as a function of the endogenous and exogenous state variables as well as their parameters at once in a single model solution. Such a "deep surrogate" (Chen et al., 2021), a high-precision approximation of an IAM based on deep neural networks, greatly accelerates the model evaluations needed for parametric uncertainty quantification. In their numerical experiments, the authors show that solving large-scale discrete-time stochastic IAMs with long-run risk and various sources of uncertainty is about $\mathcal{O}(10^5)$ times faster than in Cai and Lontzek (2019).[14]

Since the common wisdom for solving IAMs has long been that *...the nonstationary character of the problems makes value function iteration the only possible approach. The specifications of risks make these problems among the most computationally demanding ever solved in economics...* (Cai and Lontzek, 2019), we will provide some intuition about the paradigm shift that deep learning applied to IAMs allow for, following the notation of Friedl et al. (2023).

The DEQN algorithm is a simulation-based solution method using deep neural networks to compute an approximation of the *optimal policy function* $\mathbf{p} : X \to Y \subset \mathbb{R}^M$ to a dynamic model under the assumption that the underlying economy can be characterized via some first-order conditions:

$$\mathbf{G}(\mathbf{x}, \mathbf{p}) = \mathbf{0}, \ \forall \mathbf{x} \in X \subset \mathbb{R}^d. \tag{8}$$

Intuitively, DEQNs work as follows. An unknown policy function is approximated with a neural network, that is, $\mathbf{p}(\mathbf{x}) \approx \mathcal{N}(\mathbf{x})$ with trainable parameters ν, which are ex-ante unknown and that have to be determined based on some suitable loss function measuring the quality of a given approximation at a given state of the economy.[15]

[14] In addition to IAMs, deep neural networks have recently garnered the attention of economists for solving and estimating dynamic models. See Han et al. (2021), Maliar et al. (2021), Kase et al. (2022), Azinovic and Žemlička (2023), Fernández-Villaverde et al. (2023), Ebrahim Kahou et al. (2024), Payne et al. (2024), and Valaitis and Villa (2024).

[15] Neural networks are universal function approximators capable of resolving highly nonlinear features and handling large amounts of high-dimensional input data, making them a suitable candidate for approximating

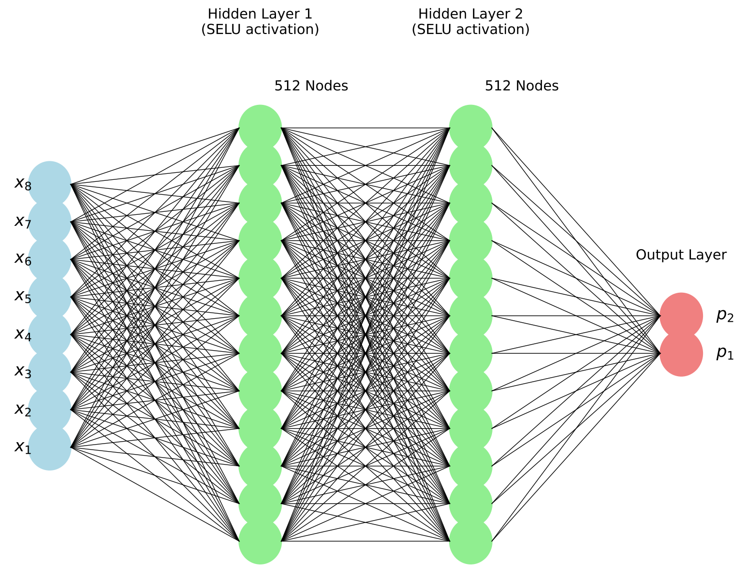

Figure 2: An FNN is used to approximate the policies of an IAM with an 8-dimensional input vector. It consists of two hidden layers, each containing 512 neurons, and an output $\mathbf{p}(\mathbf{x})$, a 2-dimensional vector.

Although there are several different types of deep neural networks, in this paper, we use densely connected feedforward neural networks (FNN). Following the literature, we define an L-layer FNN as a function $\mathcal{N}^L(\mathbf{x}) : \mathbb{R}^{d_{\text{input}}} \longrightarrow \mathbb{R}^{d_{\text{output}}}$ and say that there are $L-1$ hidden layers such that the ℓ-th layer has N_ℓ neurons. In our concrete case, $N_0 = d_{\text{input}}$ and $N_L = d_{\text{output}}$. Furthermore, for each $1 \leq \ell \leq L$, we define a weight matrix $\mathbf{W}^\ell \in \mathbb{R}^{\mathbf{N}_\ell \times \mathbf{N}_{\ell-1}}$ and bias vector $\mathbf{b}^\ell \in \mathbb{R}^{\mathbf{N}_\ell}$. Then, letting $A^\ell(\mathbf{x}) = \mathbf{W}^\ell \mathbf{x} + \mathbf{b}^\ell$ be the affine transformation in the ℓ-th layer, for some nonlinear activation function $\sigma(\cdot)$ such as `relu`, `swish`, or `selu`, an FNN is given by:

$$\mathbf{p}(\mathbf{x}) \approx \mathcal{N}(\mathbf{x}) = \mathcal{N}^L(\mathbf{x}) = A^L \circ \sigma_{L-1} \circ A^{L-1} \circ \ldots \circ \sigma_1 \circ A^1(\mathbf{x}).$$

In Figure 2, we illustrate a simple FNN with two hidden layers. The selection of hyper-parameters $\left\{L, \{N_l\}_{l=1}^L, \{\sigma_l(\cdot)\}_{l=1}^L\right\}$ is known as the architecture design. Approaches to determining these hyper-parameters include using prior experience; manual, random, or grid search; or more complex methods such as Bayesian optimization (Bergstra et al., 2011).

The DEQN algorithm to determine $\mathbf{p}(\mathbf{x})$ is started by randomly initializing the ν's, that is,

policy functions in dynamic IAMs. See, for example, Goodfellow et al. (2016) for a general introduction to deep learning, and Scheidegger et al. (2023) for an introduction in the context of economics.

an arbitrary guess for the ex-ante unknown approximate policy function. Next, one simulates a sequence of $N_{\text{path length}}$ states. Starting from some given state $\mathbf{x}_t$, the next state $\mathbf{x}_{t+1}$ is the result of the policies encoded by the neural network, $\mathcal{N}(\mathbf{x})$, and remaining model-implied dynamics.

If one knew the (approximate) policy function satisfying the equilibrium conditions, equation (8) would hold along a simulated path. However, since the neural network is initialized with random coefficients, $\mathbf{G}(\mathbf{x}_t, \mathcal{N}(\mathbf{x}_t)) \neq 0$ along the simulated path of length $N_{\text{path length}}$. This fact is leveraged to improve the quality of the guessed policy function.

Specifically, DEQNs use a loss function as the error in the equilibrium conditions, that is,

$$\ell_\nu = \frac{1}{N_{\text{path length}}} \sum_{\mathbf{x}_t \text{on sim. path}} \sum_{m=1}^{N_{\text{eq}}} \left(\mathbf{G}_m(\mathbf{x}_t, \mathcal{N}(\mathbf{x}_t))\right)^2, \tag{9}$$

where $\mathbf{G}_m(\mathbf{x}_t, \mathcal{N}(\mathbf{x}_t))$ represent all the N_{eq} first-order conditions of a given model (such as the one outlined in Section 2), that is, $\mathbf{G}(\mathbf{x}_t, \mathcal{N}(\mathbf{x}_t)) = \sum_{m=1}^{N_{\text{eq}}} (\mathbf{G}_m(\mathbf{x}_t, \mathcal{N}(\mathbf{x}_t))$.

Equation (9) is used to update the weights of the network with any variant of (stochastic) gradient descent:

$$\nu'_k = \nu_k - \alpha^{\text{learn}} \frac{\partial \ell(\nu)}{\partial \nu_k},$$

where ν'_k is the updated $k-$th weight of the neural network, and where $\alpha^{\text{learn}} \in \mathbb{R}$ is the learning rate.[16] The updated neural network-based representation of the policy is subsequently used to simulate a sequence of length $N_{\text{path\_length}}$ steps, along which the loss function is recorded, and the latter is again used to update the network parameters. This iterative procedure is pursued until $\ell_\nu < \epsilon \in \mathbb{R}$, that is, an approximate equilibrium policy, has been found.[17]

In summary, the DEQN algorithm consists of four building blocks: i) deep neural networks for approximating the equilibrium policies; ii) a suitable loss function measuring the quality of a given approximation at a given state of the economy; iii) an updating mechanism to improve the quality of the approximation; and iv) a sampling method for choosing states for updating

[16] In practical applications, *Adam* is the most popular optimizer as of 2024 (Kingma and Ba, 2014).

[17] DEQNs resemble the classical policy iteration approach for solving dynamic models (Judd, 1998). However, there are differences. Since DEQNs approximate the equilibrium functions directly, neither sets of nonlinear equations nor optimization problems need to be solved to simulate the economy. Hence, training data can be generated at virtually zero cost, which allows the user to swiftly train the neural network on more than a billion simulated states of the economy. Moreover, DEQNs provide a grid-free, global solution method, which can jointly address the computational challenges arising from a high-dimensional and irregular state space, a challenging situation for projection methods based on function approximators on high-dimensional grids (Brumm et al., 2022).

and evaluating of the approximation quality.

In the context of a DICE-like IAM, the state vector $\mathbf{x}_t$ fed into DEQN typically includes "standard" endogenous states such as capital K_t; states that track the climate, such as the masses of carbon in various reservoirs and temperature variables; time t, which accounts for the nonstationary nature of IAMs; and the vector of uncertain parameters $\vartheta \in \mathbb{R}^m$ (e.g., risk aversion). Thus, we have:

$$\mathbf{x}_t \in \mathbb{R}^{7+m} := \left(K_t, M_t^{AT}, M_t^{UO}, M_t^{LO}, T_t^{AT}, T_t^{OC}, t, \vartheta\right)^\top,$$

which is already 8-dimensional under the bold assumption that only a single parameter is uncertain. The corresponding nonlinear policies, now functions of the states and parameters, that need to be approximated in an IAM via the DEQN algorithm may include, for instance, the capital choice K_{t+1} and mitigation μ_t: $\mathcal{N}(\mathbf{x}_t) \in \mathbb{R}^2 := \left(K_{t+1}, \mu_t\right)$, and are mapped onto the DEQN as depicted in Figure 2.[18]

The computational gains of solving IAMs via deep learning over traditional methods are significant: models with potentially dozens of state variables can be solved in minutes to hours on a laptop. Furthermore, the resulting model surrogates –equilibrium policies that are functions of their economic state variables and parameters– enable computational-intensive applications, such as parametric uncertainty quantification in which statistical methods, based on an analysis of variance decomposition, measure variable importance.

However, the measures traditionally used in the literature, that is, Sobol's indices, univariate effects, and Shapley values (Owen, 2014, and Song et al., 2016), typically require, as mentioned before, tens of thousands of model solutions to obtain convergent statistics. Calculating these measures is now simplified to simple interpolations on a surrogate model. Consequently, studying large-scale stochastic IAMs and performing uncertainty quantification on them has become dramatically easier.

Finally, notice that deep learning-based approaches are not restricted to discrete-time settings but have also been proven to be promising tools for high-dimensional, continuous-time stochastic IAMs. For instance, Barnett et al. (2023) utilize an FFN combined with a deep Galerkin method to solve HJB equations and perform a model uncertainty analysis with an

[18] For details on this approach, see Friedl et al. (2023) and a related open-source code repository.

IAM including three different types of capital.

6 Macroeconomic Applications of IAMs

Researchers have used structural IAMs to provide insight into mitigating climate change and managing the green transition. For example, despite some criticism, an accurate estimation of the SCC and its evolution over time remains a crucial input for finding the right stringency of policy measures, such as carbon taxes, to internalize the climate externality efficiently. Also, we need models to design second-best policies that are politically feasible, which requires understanding who, where, and how much is affected by climate change (Gillingham and Stock, 2018). Finally, models can help avoid the "green paradox."[19] See, for example, van der Meijden et al. (2015) and Caselli et al. (2021).

Figure 3 presents a (necessarily partial) overview of the recent literature on IAMs, categorized by the models' characteristics and with specific references under each subcategory. At the top level, the diagram highlights **Dynamic IAMs**, which are used for macroeconomic applications. These models are further divided into **Global IAMs**, which focus on models with a global average climate, and **Spatial IAMs**, which incorporate spatial resolution for the analysis of local temperatures or damages in different regions. Within each of these categories, the models are further classified into **Non-Stochastic IAMs** (i.e., deterministic) and **Stochastic IAMs**, which account for uncertainty by incorporating stochastic elements into the model. Finally, each category is then divided into **Representative Agent** models, which consider a single representative agent (per region), and **Multiple Agents** models, which account for heterogeneity across agents (per region).

We now summarize some of the topics studied in papers mentioned in the diagram (and related literature).

[19] This concept was introduced by Sinn (2008), who suggests that well-intended environmental policies, such as carbon taxes or caps on emissions, that are announced in advance or are gradually implemented might lead to worse environmental outcomes in the short term. The anticipation of future regulations on fossil fuels can lead owners of these resources to increase their extraction rates before the regulations become effective, thereby accelerating greenhouse gas emissions.

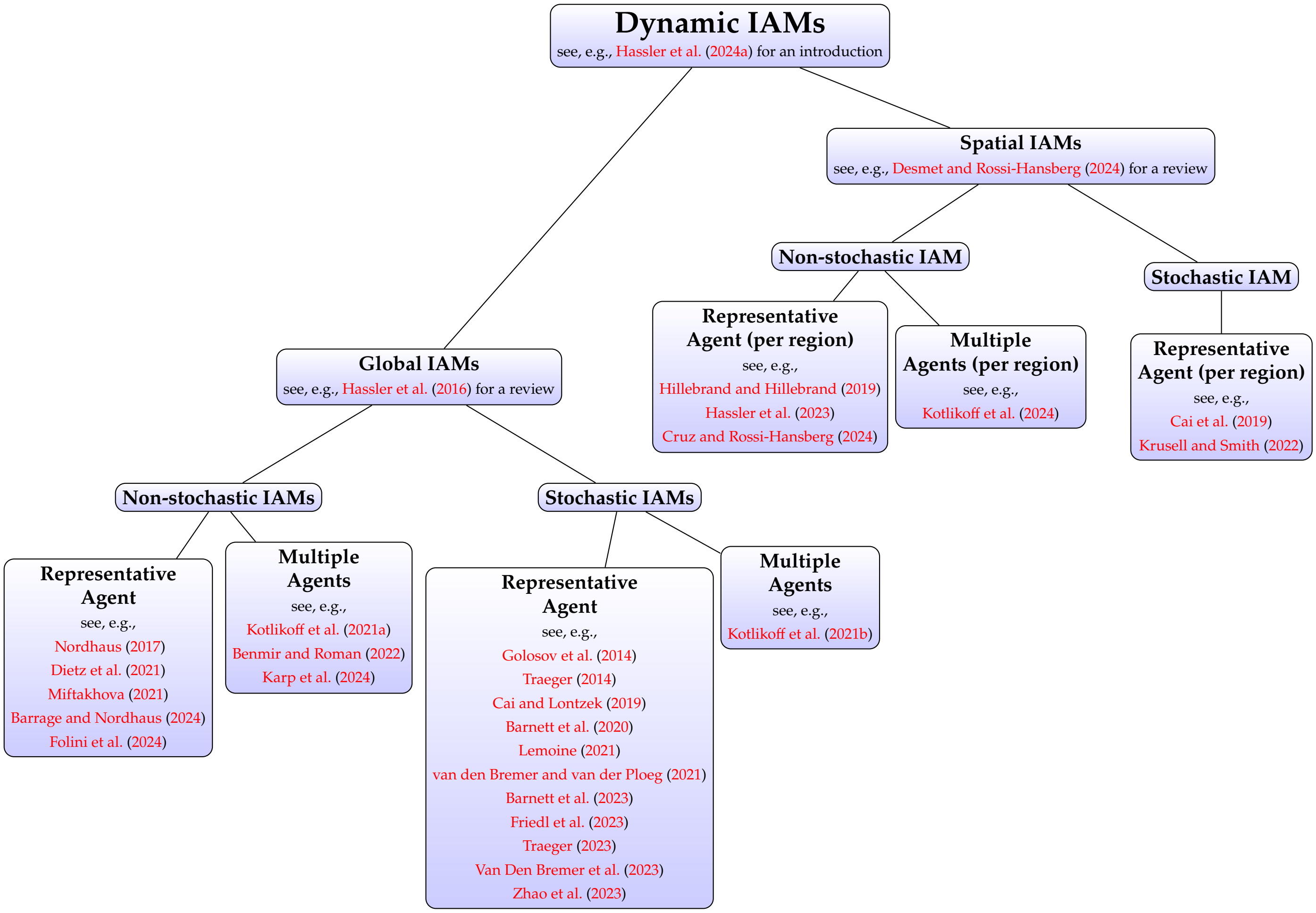

Figure 3: Overview of different types of Dynamic IAMs.

6.1 Recent Estimates on the SCC

Building on the seminal DICE model, many papers have solved various structural IAM models to compute the SCC, the related optimal policies, and its stochastic evolution and sensitivity concerning various modeling choices over time.[20] See Golosov et al. (2014), Traeger (2014), Cai and Lontzek (2019), Lemoine (2021), van den Bremer and van der Ploeg (2021), Friedl et al. (2023), Traeger (2023), van der Ploeg and Rezai (2021), Van Den Bremer et al. (2023), Barrage and Nordhaus (2024), and Folini et al. (2024). For instance, in their baseline model, Barrage and Nordhaus (2024) estimate the SCC to be approximately \$61 per ton of CO_2 for 2020 (or approximately \$0.14 per liter of gasoline). This valuation aligns with the estimates reported in comparable studies. However, these figures are contingent upon the parameters assumed in the

[20]See, also, Caselli et al. (2021) for a comprehensive overview of "low-hanging fruit" in climate policy.

model (Dong et al., 2024). This dependency underscores the need for uncertainty quantification, as advocated by Miftakhova (2021) and Friedl et al. (2023).

While the SCC alone is an invaluable input into policy, important questions also arise about the distributional consequences of climate change and climate policy across income, wealth, generations, and geographic regions. As discussed in Kotlikoff et al. (2023), a model with a representative agent, such as our prototypical structural IAM, cannot address these questions.

6.2 Robustness

Considering Knightian uncertainty is crucial in computing the SCC because it describes how we may not be able to quantify all the uncertainty probabilistically. By incorporating Knightian uncertainty, recent models provide more robust estimates of the SCC, leading to policies that adequately protect against worst-case scenarios.

For example, Zhao et al. (2023) calculate the SCC, assuming the social planner considers Knightian uncertainty. The paper introduces the concept of the "SCC robustness premium," which quantifies how much the SCC should adjust (typically upward) to account for Knightian uncertainty. The paper finds that, in a benchmark parameterization, the 2020 optimal SCC is \$162 per ton of CO_2, with a robustness premium ranging from \$1.41 to \$25.89 for variations around the benchmark.

Similarly, Barnett et al. (2020) develop a structural economic model incorporating decision theory, nonlinear impulse response functions, and dynamic valuation via asset pricing to assess the impacts of climate change and policy responses. Their analysis emphasizes the importance of accounting for model misspecification and ambiguity for policy design.

6.3 Carbon Policy Across Different Generations

Section 6.1 pointed out that carbon taxation is mostly studied in social planner or infinitely-lived-agent models. This modeling choice obscures, for instance, the potential of carbon taxation to have different effects across generations.

Kotlikoff et al. (2021a) use an OLG model to calculate the carbon-tax policy delivering the highest uniform welfare gain to all current and future generations. Their model features coal, oil, and gas, increasing extraction costs, clean energy, technical and demographic change, and carbon/temperature/damage functions. Assuming high-end carbon damages, they find that the optimal carbon tax is $70, rising annually at 1.5%. This policy raises all generations' welfare by almost 5% – a "win-win" policy. However, doing so requires major intergenerational redistribution. Similar ideas are presented in Karp et al. (2024).

Using a life-cycle model, Fried et al. (2018) evaluate the welfare impact of different schemes to distribute carbon tax revenue on future agents vs. those alive at the policy's inception. While using carbon tax revenues to reduce existing distortionary taxes minimizes non-environmental welfare costs for future agents, providing lump-sum rebates offers the greatest welfare benefit for current generations, providing a clear insight into both long-term outcomes and transitional effects of different policy options.

Fried et al. (2024) present a general equilibrium life-cycle model to assess the welfare and distributional effects of various methods for redistributing carbon tax revenue to households. The welfare-maximizing strategy uses two-thirds of the revenue to lower distortionary capital income taxes and one-third to enhance the progressivity of labor income taxes.

6.4 Carbon Policy Across Regions

While the planet has warmed by approximately 1.1°C on average since the dawn of the Industrial Revolution, various regions have experienced this warming more severely. Moreover, the most affected regions are not the wealthiest ones (Desmet and Rossi-Hansberg, 2024). This point suggests the importance of implementing multi-regional IAMs, as pioneered by the Regional Integrated Model of Climate and the Economy (RICE) (Nordhaus and Yang, 1996). However, doing so presents technical challenges. Multi-regional IAMs require a spatial economic framework and the scaling of climate emulators and damage functions to the local level.

Nonetheless, multi-regional IAMs have taught us the importance of considering distributional aspects in the design of optimal climate policies. For example, RICE was used to evaluate national approaches to climate policy, including market-driven solutions, cooperative strategies, and noncooperative tactics. The model findings indicate that cooperative strategies reduce emissions more than noncooperative approaches. Further, there is notable variation in the degree of policy enforcement between cooperative and noncooperative strategies across different countries: high-income countries might incur greater losses from cooperation.

More recent work by Krusell and Smith (2022) makes a similar point. The authors develop a detailed global economy-climate model with high geographic resolution to analyze the impacts of climate change across approximately 19,000 regions. Each region adapts its consumption, savings, and energy use in response to local climate changes and productivity shifts, which are influenced by regional temperatures following an inverted U-shaped relationship with productivity. While global effects of climate change are negative, they are significantly less than the variations experienced regionally, with some regions benefiting and others suffering. The study finds that a carbon tax improves global welfare on average, but has unequal impacts across regions. Lastly, climate change greatly increases global inequality.

Kotlikoff et al. (2024) introduce a detailed, annually updated multi-region OLG model for studying climate change and carbon policy using region-specific temperature effects and damage estimates. The results indicate that climate change could severely impact GDP, especially in India, Brazil, and the South Asian Pacific. The paper models a carbon taxation strategy, along with targeted regional and generational transfers, and finds this package of Pigouvian taxes and transfers reduces emissions and improves welfare by 4.3% across regions. However, achieving uniform welfare improvements across regions requires high compensatory costs from future generations in some areas. A revised policy that limits these burdens to under 10% of consumption could still enhance welfare by at least 4.0% globally. Nevertheless, all major emitters, particularly China, must adopt carbon taxes immediately to combat climate change effectively.

Hillebrand and Hillebrand (2019) present a dynamic general equilibrium model with multiple regions to explore the economic impacts of climate change under varying policies. The model highlights that the optimal climate policy consists of an emissions tax, which is independent of the interests of different countries. In contrast, transfers must follow a more complex schedule to maximize welfare. In other words, the study suggests that the main political challenge lies not in establishing the tax policy but in determining how to allocate the burden of climate change through transfers.

Cruz and Rossi-Hansberg (2024) develop a dynamic economic model of the global economy with a high spatial resolution to analyze the local economic effects of global warming. Their model incorporates adaptations such as trade, migration, innovation, and changes in natality rates and quantifies impacts on regional productivity and amenities due to temperature changes. The findings reveal large spatial heterogeneity in welfare losses, with some regions experiencing severe declines while others might benefit. The study also evaluates the effectiveness of carbon taxes, abatement technologies, and subsidies in mitigating climate impacts, highlighting the importance of innovation and migration as adaptation mechanisms. Overall, spatial inequality increases, and while the uncertainty in average welfare effects is considerable, the relative losses across regions are more predictable.

6.5 Green Energy Transition

Hassler et al. (2021, 2024a), among others, argue that one needs to consider the significant uncertainty surrounding the magnitude and impact of climate change. In particular, policymakers should anticipate the possibility that ex-post errors are inevitable. Hassler et al. (2021), for instance, study the implications of setting a global carbon tax at incorrect levels. Interestingly, the authors document that errors resulting from overly pessimistic views on climate change are significantly less detrimental than those stemming from excessive optimism. This finding suggests that policymakers should tilt their expectations toward worse outcomes when setting up the transition toward a net-zero economy.

A growing strand of the literature enriches models of asset pricing and monetary and macroprudential policies by bringing in climate change. Motivated by the California cap-and-trade market, Benmir and Roman (2022) examine the distributional effects of the U.S. achieving its net-zero emissions target by 2050. Using a heterogeneous household economy model, they show that the net-zero policy boosts long-term welfare but brings short- to medium-term costs, quantified as a 0.54% welfare gain in consumption terms vs. a laissez-faire scenario, with a 6-10% rise in financially constrained households by 2050. It also explores how revenue redistribution from carbon policies could ease consumption losses and aid the transition.

Benmir et al. (2020) examine the design of a carbon tax where CO_2 emissions impact the marginal utility of consumption, finding that the optimal tax aligns with the shadow price of CO_2 emissions, estimated as pro-cyclical using asset-pricing theory. Consequently, the optimal carbon tax cools the economy during booms and stimulates it during recessions, affecting asset prices and welfare based on the emission-abatement technology used.

Annicchiarico et al. (2023) analyze the effectiveness of a carbon tax versus a cap-and-trade scheme using a DSGE model that accounts for environmental externalities and financial intermediation. They find that financial market distortions significantly influence climate policy effectiveness, with cap-and-trade offering lower welfare costs during business cycles, especially under conditions of high financial frictions and firm leverage, and substantial risk aversion among agents. Additionally, implementing macroprudential policies can minimize these differences by alleviating financial distortions, helping to stabilize business cycles, and making performance outcomes of different climate policies more comparable.

As climate change intensifies, central banks face challenges from "climateflation," caused by the negative economic impacts of global warming, and "greenflation," arising from the inflationary effects of climate mitigation policies. In this context, Sahuc et al. (2023) develop and estimate a nonlinear New Keynesian climate model to examine these phenomena. They show that a central bank can decrease inflation associated with the green transition at the cost of reduced output expansion. However, the medium-term sacrifices are justified for long-term price stability.

In a related fashion, Nakov and Thomas (2023) investigate how climate change mitigation, such as carbon taxes, impacts optimal monetary policy within a New Keynesian model that incorporates climate externalities. If carbon taxes are implemented at their socially optimal levels, they harmonize with monetary policy goals, allowing for complete stabilization of inflation and the output gap without trade-offs. However, when carbon taxes are suboptimal, monetary policy faces trade-offs between its core objectives and climate goals. However, these are predominantly resolved in favor of maintaining price stability even during prolonged transitions to optimal taxation. The study further explores a model extension where, in the presence of financial frictions, it becomes optimal for central banks to preferentially purchase green corporate bonds, which supports the green transition, albeit with limited impact on CO_2 emissions and global temperatures due to the minor role of bond spreads.

Another key topic for mitigating climate change is the technological diffusion of clean technologies and endogenous growth. Acemoglu et al. (2012) incorporate endogenous and directed technical change into an environmentally constrained growth model, using both dirty and clean inputs for production. They find that sustainable growth is feasible with temporary taxes/subsidies that promote clean inputs when these are substitutable. The optimal policy requires a balance of carbon taxes and research subsidies to prevent carbon tax overuse. Additionally, delaying intervention leads to costly extended periods of slow growth during the transition, and utilizing an exhaustible resource for dirty input production encourages a shift to clean innovation in a laissez-faire environment.[21]

Campiglio et al. (2022) explore the complex dynamics of transitioning from a high- to low-carbon economy, analyzing the adjustment costs of switching from fossil-fuel-based to clean capital, along with technological advances and variabilities in economic and climatic conditions. Using a model that includes emissions abatement costs sourced from an extensive energy database, the authors argue that an optimal transition involves significant repurposing and stranding of existing industrial capital, like power plants and steel mills, due to the high costs of rapid greenhouse gas reduction and capital inertia. Despite immediate high emissions, advancements in clean technologies and uncertainties in climate and economic factors contribute to reduced emissions and cooler temperatures over time, justifying a 33% higher optimal carbon price today compared to a simpler model without these complex dynamics.

Finally, there is also important work on transition risks and stranded assets using macro models such as van der Ploeg and Rezai (2020) and Hambel and van der Ploeg (2024).

7 Conclusion

Substantial progress has been made over the past decade in understanding the economics of climate change. We now have computational tools and data that are vastly better than a decade ago and are continuing to improve, providing valuable new insights for policy discussions on the transition toward a green economy.

The evolving climate policy landscape increasingly acknowledges the critical role of integrating economic and (macro-)financial expertise. The shift toward involving finance professionals (Kollenberg and Taschini, 2016, Kölbel et al., 2022, and Hambel and van der Ploeg, 2024) alongside macroeconomic and trade analysts (Jondeau et al., 2022, and Arkolakis and Walsh, 2023) is pivotal for designing effective subsidies, tax incentives, and investment strategies in renewable energies and technologies (Egli et al., 2018). This integration aims to ensure that economic incentives align with environmental targets, thereby mitigating the political and economic repercussions of abrupt changes in energy prices.

For instance, almost all work in the literature finds that the estimated SCC is highly sensitive

[21] One can also study technological innovation from the perspective of how consumers' environmental concerns affect firms' decisions to innovate in "clean" technologies (Aghion et al., 2023), but this phenomenon is beyond our scope.

to the modeler's choice of the social discount rate (SDRs). There is a major debate in the literature about the most solid value for the SDRs (Arrow et al., 2014). Recent work by Bauer and Rudebusch (2023) and others points out that the equilibrium or steady-state real interest rate has significantly decreased since the 1990s, leading to a lower term structure of SDRs. This insight would suggest weighing future damages from climate change more highly and, thus, using a higher SCC and a more aggressive climate policy (Rennert et al., 2022).

As this trend of integrating macroeconomics with other areas of economics and natural science gains momentum, the new generation of structural IAM models is expected to become more central to climate policies, supporting more sustainable management of broader Earth systems such as water, food, and biodiversity (Giglio et al., 2023). Much important work will come during the next few years.

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