Integrated assessment modelling - Big and small

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Climate macroeconomics & finance 2024/25 - Lecture 8

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Last lectures

- We want to explore possible climate/transition futures
  - $\rightarrow$ We need models
  - The godfather of climate economic models: DICE
  - However: limitations
- Alternative strategies
  - Include macro-finance into climate economic models
  - Include climate/transition into neoclassical macro models
  - Include climate/transition into non-neoclassical macro models

Today's lecture

- Integrated Assessment Models (IAMs)
    - Integrate economy, energy and climate
    - Going beyond DICE
- Analytical IAMs
    - Small-scale models rooted in econ
    - Useful to explore new grounds (e.g. uncertainty)
    - Incorporating insights from financial modelling
- Large-scale numerical IAMs
    - Diversified family of numerical models (including CGEs)
    - Going granular on technologies/regions/sectors
    - Intermodel comparison exercises $\rightarrow$ IPCC scenarios
    - Spatial IAms

Analytical IAMs

Analytical IAMs

- By ‘analytical’ IAMs, we refer to a family of models
  - Integrating economy and climate/transition small-scale (without granularity of large numerical IAMs) and with simplified functions
  - Aimed at deriving analytical conclusions (e.g. a formula for the optimal carbon price) or at investigating specific mechanisms
  - Rooted into neoclassical growth theory
  - Used to introduce new advancements and features (e.g. Epstein-Zin preferences, stochastic uncertainty, learning)
  - While analytical, they also often offer numerical simulations
  - Usually published in econ journals (while large IAMs often appear on interdisciplinary ones)

Analytical IAMs interests

- Find efficient transition/policy paths
  - Can be in a cost-benefit setting with climate damages (see Golosov et al., 2014 in Econometrica).. .. or in a cost-effectiveness one, i.e. looking for least-cost paths (see Lemoine and Rudik, 2017 in AER)
- Introduce uncertainty and learning
  - 'Recursive IAMs': focus on uncertainty (Cai & Lontzek, 2018 in JPE; van den Bremer & van der Ploeg, 2021 in AER)
    - Deterministic models or Monte Carlo simulations not enough
    - We need to find optimal paths under uncertainty (i.e. behaviour should respond to uncertainty and its resolution)
  - Stochastic elements: Brownian and Poisson processes
- Incorporate insights from macro and finance
  - Ongoing efforts build on modelling approaches borrowed from macro/financial economics (e.g. Epstein-Zin preferences)
  - Overlaps with E-DSGE and asset pricing models (Lecture 9)

Golosov et al. (2014) in Econometrica (i)

- Logarithmic utility function ($\eta = 1$)

$$U_t(C_t) = \ln C_t$$

- Cobb-Douglas production function (pre-damage output)

$$\tilde{Y}_t = A_t K_t^{\alpha} N_t^{1-\alpha-\nu} E_t^{\nu}$$

where K: capital; N:labour; E: energy composite

- CES energy function with oil, coal and clean sources

$$E_t = \left(\kappa_{\text{coal}} E^{\rho}_{\text{coal},t} + \kappa_{\text{oil}} E^{\rho}_{\text{oil},t} + \kappa_{\text{clean}} E^{\rho}_{\text{clean},t} \right)^{\frac{1}{\rho}}$$

- Fossil emissions E^f increase CO2 atmospheric concentration S

$$(S_t - \bar{S}) = \sum_{s=0}^{t+T} (1 - d_s) E^f_{t-s}$$

with $1 - d_s$ amount of carbon in atmosphere at time s

Golosov et al. (2014) in Econometrica (ii)

- Carbon cycle: a share φ_l remains forever; $1-\varphi_0$ decays immediately; the rest decays at rate φ

$$1 - d_s = \varphi_L + (1-\varphi_L)\varphi_0(1-\varphi)^s$$

- Damages proportional to output

$$Y_t = (1 - D_t)\tilde{Y}$$

- Damage function of CO2 concentration

$$1 - D_t = e^{-\gamma(S_t - \bar{S})}$$

with γ defining climate damage strength (lower γ, higher loss)

- Planning problem:

$$\max \mathbb{E} \sum_{t=0}^{\infty} \beta^t U(C_t)$$

Golosov et al. (2014) analytical results

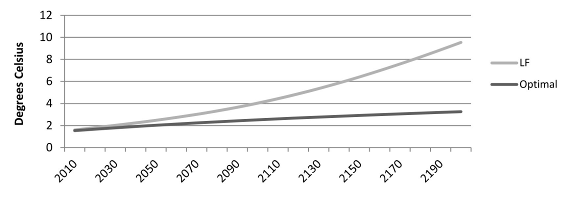
- Assuming constant savings rate, the marginal damage from emissions is a function of (i) discounting (ii) damage coefficient (iii) atmospheric carbon depreciation structure

$$\Lambda_t^s = Y_t \left[\mathbb{E} \sum_{j=0}^{\infty} \beta^j \gamma_{t+j} (1 - d_j) \right]$$

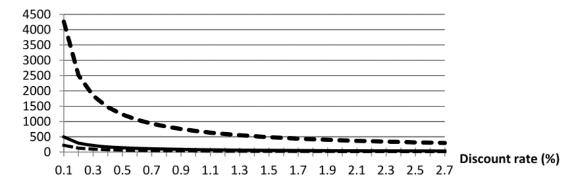
- Decentralized equilibrium: Pigouvian carbon tax equal to Λ^s
- Optimal carbon tax grows at the growth rate of the economy

Golosov et al. (2014) numerical results

- Numerical simulations
  - Stochastic uncertainty around true value of γ



Optimal vs lassez-faire temperature. Source: Golosov et al. (2014)



Optimal tax rates ($ per ton of carbon at 70$tn output) before uncertainty is resolved (solid) and after (dashed: γ_L and γ_H). Source: Golosov et al. (2014)

Alternative: put constraint and find efficient path

- Hotelling structure applicable
  - Hotelling rule: optimal net price ('Hotelling rent') of an exhaustible resources grows at the rate of interest
  - Remaining allowable CO2 emissions (carbon budget) are like an exhaustible resource
  - Many regions (e.g. Europe) don't run cost-benefit analysis ($\rightarrow$ SCC) but focus on keeping T below a target
- Optimal carbon price is a function of interest rate (or SDR)
  - $P_t = e^{\rho t} P_0$ (continuous time)
  - $P_t = \left(\frac{1}{1+\rho}\right)^t P_0$ (discrete time)
- Risk-adjusted interest rate is what we're interested in
  - Gollier et al. (2024): 3.5%
  - If it's too high, it means that, for a specific carbon budget, price today is too low

Lemoine and Rudik (2017) in AER

- CO2 concentration M increases with net emissions $(E - A)$ and decreases with decay

$$\dot{M}(t) = E - A(t) - \delta\left(M(t) - M_{\text{pre}}\right)$$

- Concentration generates forcing F but this translates into temperature change with some inertia (greater ϕ, lower inertia)

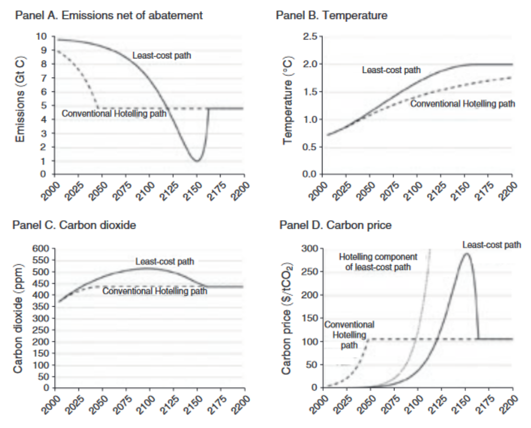
$$\dot{T}(t) = \phi\left[sF(M(t)) - T(t)\right]$$

- Planner minimises abatement costs $C(A)$

$$\min_{A(t)} \int_{t_0}^{\infty} e^{-r(t-t_0)} C(A(t))\, dt$$

Lemoine and Rudik (2017) results

- Least-cost path targeting $\bar{T}$ different from Hotelling path constraining emissions
    - Overshoot of atmospheric concentration allowed
    - Postpone climate policies



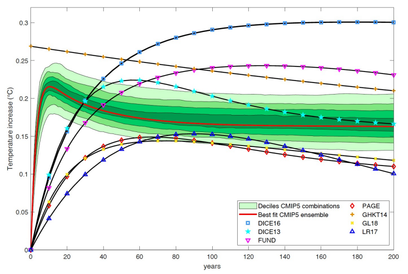
Least-cost and Hotelling trajectories with a 2° temperature target. Source: Lemoine et al. (2017)

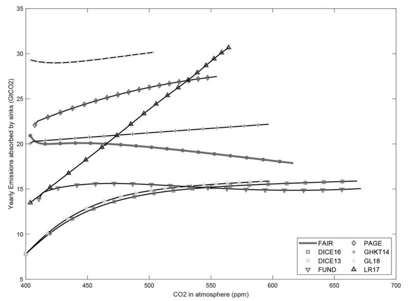
Are IAMs getting climate dynamics right? (i)

- Dietz et al. (2021) take six prominent IAMs
    - DICE, FUND and PAGE; Golosov et al. (2014) on Ecta; Lemoine and Rudik (2017) on AER; Gerlagh and Liski (2018) on EconJ
    - Compare them with climate science models from CMIP5
- First experiment: how does T react to an emission impulse?
    - We know from climate science: rapid increase and stable afterwards
- Second experiment: how does CO2 absorption change when concentration increases?
    - We know from climate science: absorption decreases when concentration rises

Are IAMs getting climate dynamics right? (ii)

- IAMs tend to follow slower temperature response trajectories, and not include decline in sinks absorption capacity
- → Optimal carbon prices too low
- → Optimal carbon prices too sensitive to discount rates

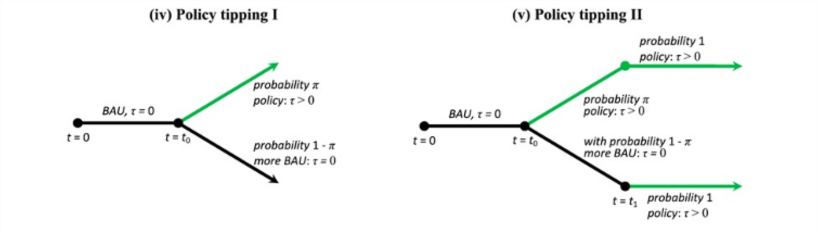




Source: Dietz et al. (2021)

Stranding: van der Ploeg & Rezai (2020) in JEEM

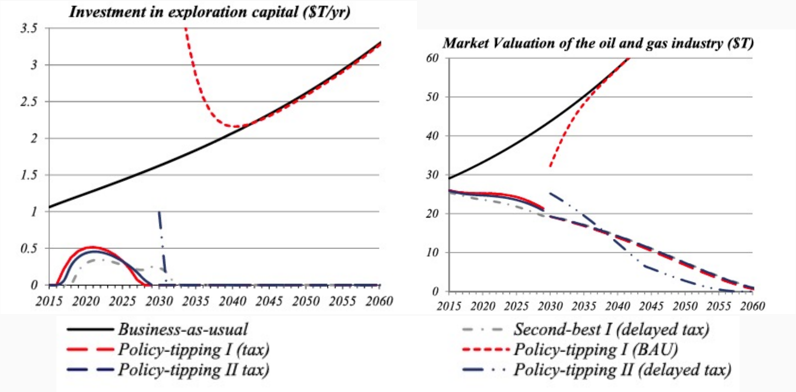
- Focus on the fossil fuel sector
  - A single type of capital to work with: extraction capital k
  - No underutilisation of capital allowed
- Market valuation of fossil firms given by future profits
  - They decide investments by maximising $V^R \equiv \int_0^\infty e^{-rt}\Pi^R$
- Policy tipping setting:



Source: van der Ploeg & Rezai (2020)

van der Ploeg & Rezai (2020): Results

- Uncertainty (and its resolution) affect transition profiles
  - I might go to zero but K continues to operate
  - $\rightarrow$ V moves more smoothly



Source: van der Ploeg & Rezai (2020)

Campiglio, Dietz and Venmans, 2024 (i)

- Cobb-Douglas production function with abatement costs Λ and damages Ω

$$Y = AL^{1-\alpha}K^{\alpha}\Lambda\Omega$$

- Two types of capital stocks with different productivities
  - Abatement takes place via structural change $K_d \rightarrow K_c$
  - Negative dirty investments possible ('stranding')
  - Adjustment costs in both investments and disinvestments
- Emissions function of dirty capital

$$E = \psi_t K_d$$

- Damages are a function of temperature T, itself a function of cumulative emissions S (with ζ: TCRE coefficient)

$$\Omega = \exp\left(-\frac{\gamma}{2}T^2\right)$$

Campiglio, Dietz and Venmans, 2024 (ii)

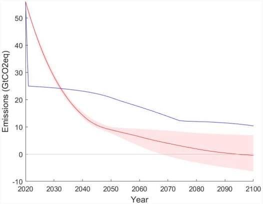
- Abatement cost function of abatment μ and MAC slope φ

$$\Lambda = \exp\left(-\frac{\varphi_t}{2}\mu^2\right)$$

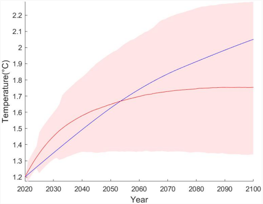
- Clean technology costs fall over time
  - Exogenous component: spillovers from general tech progress: AI, nanotechnology, etc.
  - Endogenous component: MAC parameters evolve as a function of cumulative abatement M (learning)
- Sources of uncertainty
  - Brownian motions on temperature, capital stocks and productivity
  - T-dependent Poisson jumps on productivity (macro disasters)
- Epstein-Zin-Weil recursive preferences

Campiglio, Dietz and Venmans (2024) results (i)

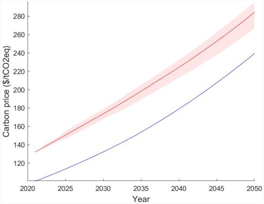
- CB carbon price: \$133 $\rightarrow$ \$283 (2050)
- CB disinvestment: \$4.8 tn. (33% lost)
- Not considering inertia, learning and uncertainty gives incorrect suggestions



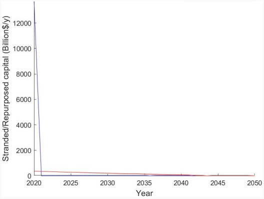
(a) Emissions E



(b) Temperature T



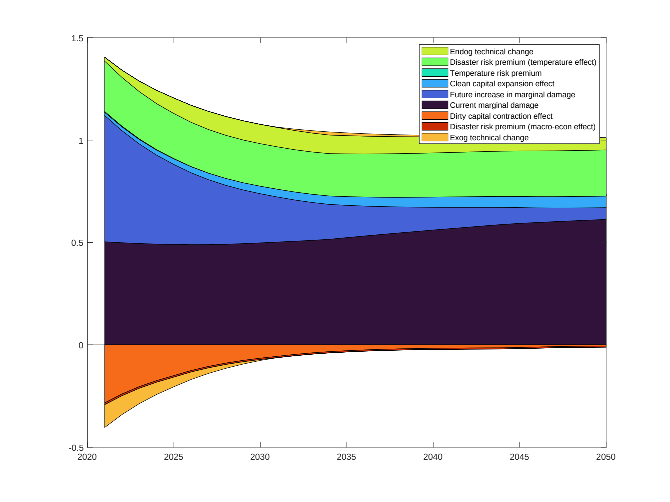
(c) Carbon price p



(d) Dirty capital disinvestment R

Comparison with 'straw man' model. Red: cost-benefit. Blue: without inertia, learning and uncertainty. Source: Campiglio et al. (2024)

Campiglio, Dietz and Venmans (2024) results (ii)



Optimal carbon price decomposition results. Y-axis is scaled in percent of the absolute price. Source: Campiglio et al. (2024)

Strengths and weaknesses of analytical IAMs

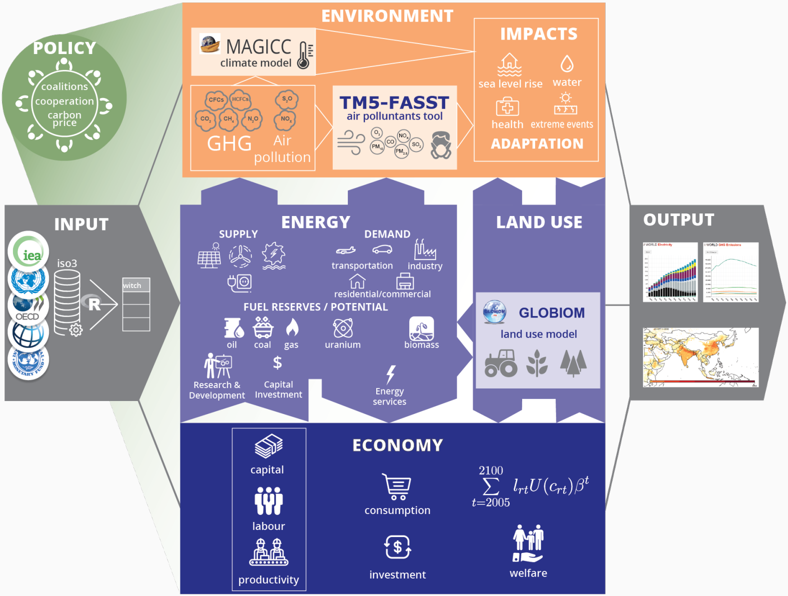
- They are useful, in that they
  - offer interesting new insights, especially on uncertainty-related matters, which would not be possible in large-scale numerical models
  - provide analytical conclusions (more generally valid than numerical ones)
  - develop a bridge between climate economics and macro/finance modelling
- At the same time, they
  - are by definition constrained in their complexity and need to be simple

Large-scale numerical IAMs

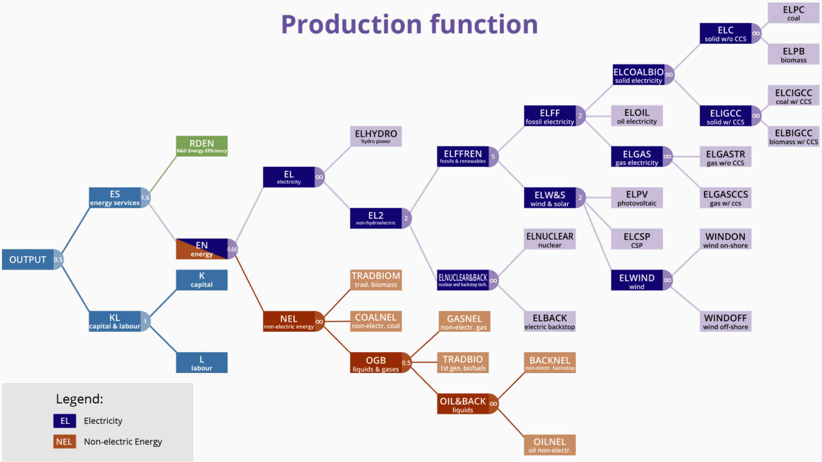
Large-scale numerical IAMs

- Common features across models
  - Multiple regions
    - Cooperative/non-cooperative behaviour; coalitions
    - Equity issues (burden-sharing, transfers)
  - Detailed energy sources/technologies and pollutants
  - Small climate modules (or links to larger climate models)
  - Economic modules also tend to be simple (or absent)
    - Exception: CGE models (are they IAMs?)
- But large variability across models
  - Partial vs general equilibrium
  - Simulation vs optimization
  - Recursive dynamic (myopic) vs intertemporal optimization (foresight)
  - Different representation of climate impacts, non-energy sectors, land use, regions..

An example: The WITCH model



The WITCH production function



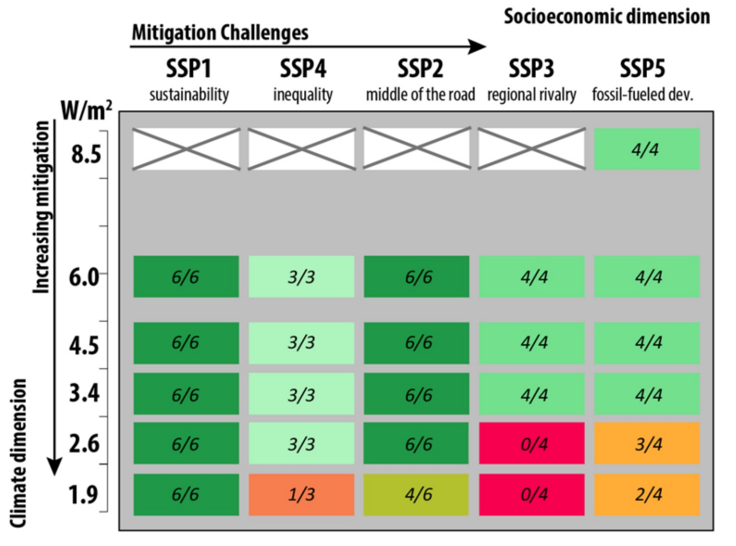
Source: WITCH website

- More details in the WITCH documentation

Many other large IAMs exist

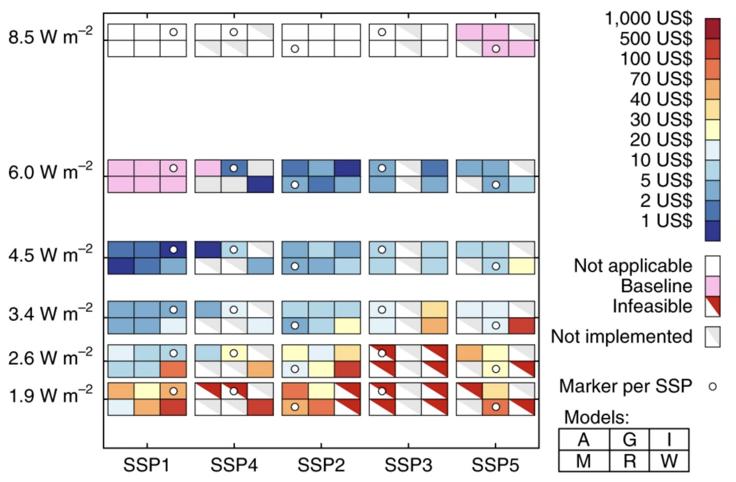
- Other notable models:
  - MESSAGE model (IIASA, Austria)
  - GCAM model (JGCRI, United States)
  - IMAGE (PBL, Netherlands)
  - REMIND model (PIK, Germany)
  - IMACLIM (CIRED, France)
  - E3ME (Cambridge Econometrics, United Kingdom)
  - An overview: see the IAM Consortium Wiki paper
- Inter-model comparison exercises
  - Run the same scenarios and compare results
  - e.g. Rogelj et al. (2018): can we achieve 1.5°C? using six IAMs

SSP/RCP combinations



In cells: numbers of models with feasible scenarios. Source: Rogelj et al. (2018)

Optimal carbon prices per RCP/SSP



Average global average carbon prices over 2020–2100 (discounted to 2010 with a 5% rate). A: AIM/CGE; G: GCAM4; I: IMAGE; M: MESSAGE-GLOBIOM; R: REMIND-MAgPIE; W: WITCH-GLOBIOM. Source: Rogelj et al. (2018)

Fossil stranding using TIAM-UCL

- TIAM-UCL regional model:
  - Partial equilibrium model with detailed representation of energy sources and systems
  - Driven by minimisation of energy system NPV costs to 2100
- What is the optimal geographical distribution of unnburnable carbon in a 2° scenario?

Table 1 | Regional distribution of reserves unburnable before 2050 for the 2 °C scenarios with and without CCS

	2 °C with CCS						2 °C without CCS					
	Oil		Gas		Coal		Oil		Gas		Coal	
Country or region	Billions of barrels	%	Trillions of cubic metres	%	Gt	%	Billions of barrels	%	Trillions of cubic metres	%	Gt	%
Africa	23	21%	4.4	33%	28	85%	28	26%	4.4	34%	30	90%
Canada	39	74%	0.3	24%	5.0	75%	40	75%	0.3	24%	5.4	82%
China and India	9	25%	2.9	63%	180	66%	9	25%	2.5	53%	207	77%
FSU	27	18%	31	50%	203	94%	28	19%	36	59%	209	97%
CSA	58	39%	4.8	53%	8	51%	63	42%	5.0	56%	11	73%
Europe	5.0	20%	0.6	11%	65	78%	5.3	21%	0.3	6%	74	89%
Middle East	263	38%	46	61%	3.4	99%	264	38%	47	61%	3.4	99%
OECD Pacific	2.1	37%	2.2	56%	83	93%	2.7	46%	2.0	51%	85	95%
ODA	2.0	9%	2.2	24%	10	34%	2.8	12%	2.1	22%	17	60%
United States of America	2.8	6%	0.3	4%	235	92%	4.6	9%	0.5	6%	245	95%
Global	431	33%	95	49%	819	82%	449	35%	100	52%	887	88%

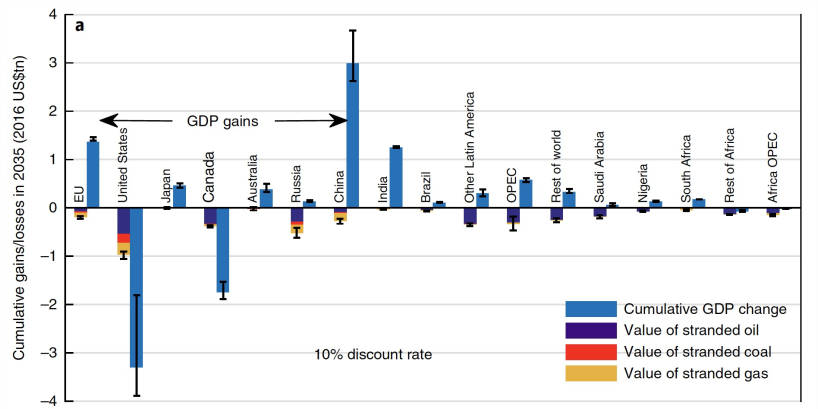
FSU, the former Soviet Union countries; CSA, Central and South America; ODA, Other developing Asian countries; OECD, the Organisation for Economic Co-operation and Development. A barrel of oil is 0.159 m^3; %, Reserves unburnable before 2050 as a percentage of current reserves.

Source: McGlade and Ekins (2015)

Fossil stranding using E3ME

- Combination of E3ME (macroeconometrics), FTT (diffusion) and GENIE (Earth systems) models
- Two stranding drivers: 2°C climate policy or technological diffusion
    - Fossil stranding can happen even without policies
    - Drop in demand for fossil fuels ($\rightarrow$ can trigger a 'sell out')
- Focus on geographical distribution of fossil stranding and macro implications
    - Net importers (e.g China, EU) may benefit from dynamics
    - Producers (Russia, US, Canada) will lose out
    - Global NPV wealth loss of US$1-4 trillion

Fossil stranded assets across regions



Cumulative GDP changes and discounted fossil fuel value loss to 2035 - 2 °C sell-out scenario vs IEA projections. Source: Mercure et al. (2018)

Strengths and weaknesses of numerical IAMs

- IAMs are very useful
  - Granular representation of technologies, calibrated on real data, multi-regional perspective
  - Inter-model comparison gives us idea of uncertainty ranges
- However
  - Doubts about theoretical foundations
  - Economic modules usually very small and simple
  - Difficult to introduce macro and financial components into modelling frameworks

Computable General Equilibrium (CGE) models

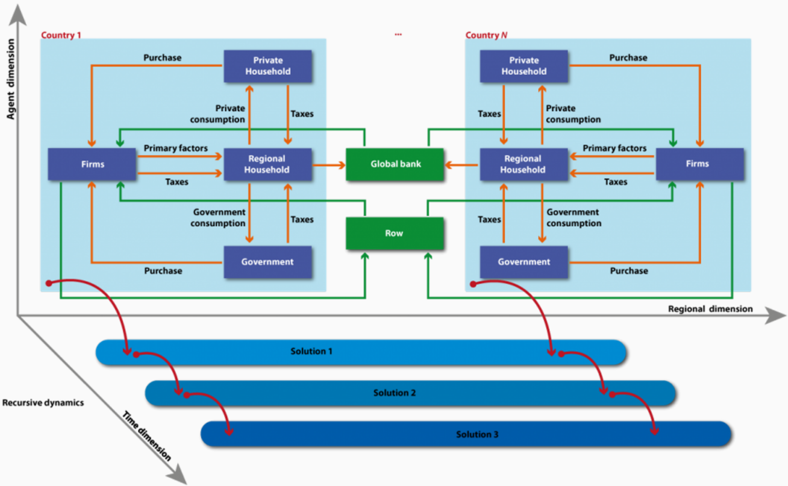
CGE models

- Start from actual data capturing economic inter-dependencies
  - Input-Output (IO) tables
  - Social Accounting Matrices (SAM) also include institutional accounts
  - e.g. GTAP Database
- Define a set of behavioural rules
  - Profit maximisation or cost minimisation by firms
  - Welfare maximisation by households
  - e.g. GTAP model
- Calibrate parameters on available data
  - E.g. Armington elasticity (of substitution between products of different countries)
- Introduce a change
  - E.g. a change in taxes or border tariffs
  - Observe how the system reacts to the change in prices

CGE models in climate economics

- They can adapted to include energy/environment
  - Impact of mitigation policies (carbon tax) or climate impacts
  - Multi-sectoral dimension is important (structural change)
  - Multi-regional dimension is important (trade impacts)
- Stylized representation of macro-financial dimension
  - All savings aggregated into a global banks that reallocates them according to relative returns
  - Crowding-out assumption (exogenous money)
- Example: ICES model (CMCC Venice)
  - Recursive model generating a sequence of static equilibria under myopic expectations
  - Derived from GTAP-E model
  - Cost-minimizing firms, representative household and government

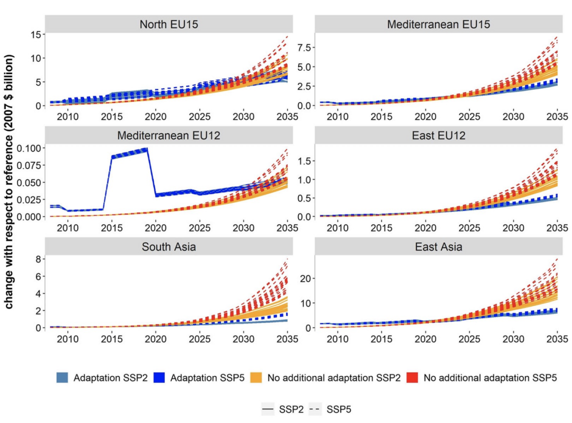
An example: the ICES model



ICES model structure. Source: ICES website

An application: Public deficit and adaptation to sea level rise

- Public spending in SLR adaptation increases deficits in the short-term but avoids larger deficits in the longer-term
- Note: total crowding-out of investments assumed



Impacts on public deficit. Source: Parrado et al. (2020)

Strengths and weaknesses of CGEs

- Clear advantages, as they
  - Capture inter-sectoral and inter-regional exchanges in a dynamic setting
- However, they
  - Rely on unrealistic market clearing assumptions (in the real world, we have inefficiencies and underutilisation)
  - Given these assumptions, it's hard to introduce further macro/financial dimensions

Spatial IAMs

Spatial IAMs

- Spatial IAMs (S-IAMs)
    - Climate change impacts diversified across space (see Lecture 2)
    - Migration/trade as adaptation mechanism
    - Recent literature using developments in spatial economics (see Desmet and Rossi-Hansberg, 2024)
- Two-dimensional space
    - Latitude and Longitude
    - 1°x1° grids: 64,800 cells (locations r) in the globe
    - Data on population, output, temperature
    - Harder to split sectors: agriculture vs non-agriculture

Desmet and Rossi-Hansberg (2024) in Annu. Rev. Econ. (i)

- Location-specific utility for agent j function of consumption C, local amenities a, preference for location ε and possibly access cost to location ('migration costs') m

$$U_t^j(r) = a_t(r) C_t(r) \epsilon_t^j(r) m_t^j(r)^{-1}$$

- Local amenities can be made a function of climate change T and affected by congestion (too many people L)

$$a_t(r) = \bar{a}(r, T_t) L_t(r)^{-\lambda}$$

- Consumption combines goods from different industries i, each with several varieties (firms) ω

$$C_t(r) = \prod_{i=1}^{I} \left(\int_0^1 c_{it}^{\omega}(r)^{\rho} d\omega \right)^{\frac{\chi_i}{\rho}}$$

with ρ: elast. of sub. btw varieties; χ_i: exp. share of good i

Desmet and Rossi-Hansberg (2024) in Annu. Rev. Econ. (ii)

- Firm/variety production q in industry i is a Cobb-Douglas function of k inputs with (T-affected) productivity z

$$q_{it}^{\omega}(r) = z_{it}^{\omega}(r) \prod_{k} F_{kit}(r)^{\mu_{ki}}$$

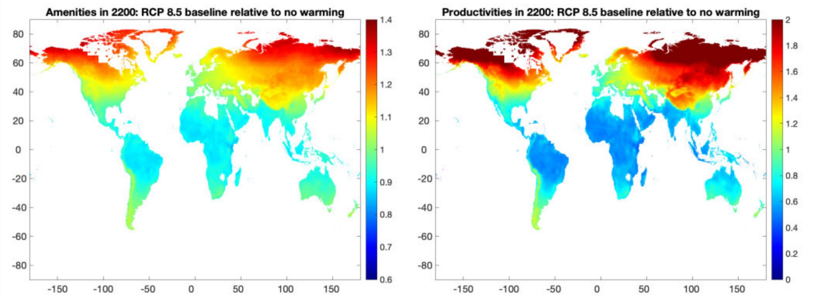
- Production inputs
  - Labor, land, energy and others
  - Capital stocks usually missing
  - Example from Cruz and Rossi-Hansberg (2024)

$$q_t^{\omega}(r) = \phi_t^{\omega}(r)^{\gamma_1} z_t^{\omega}(r) \left(L_t^{\omega}(r)^{\chi} e_t^{\omega}(r)^{1-\chi} \right)^{\mu}$$

  with ϕ: innovation

Desmet and Rossi-Hansberg (2024) results

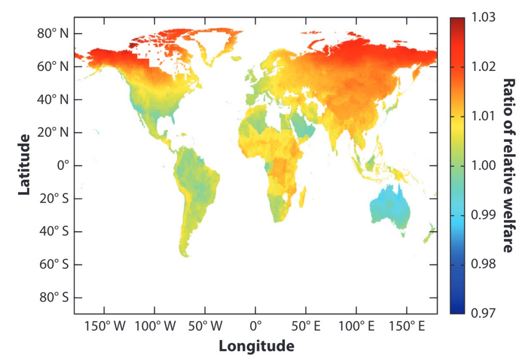
- Climate change has strongly diversified impacts across space



Ratio between amenities and productivities in 2200, RCP8.5 climate change scenario vs no climate change. Source: Cruz and Rossi-Hansberg (2024)

Desmet and Rossi-Hansberg (2024) results

- Adaptation by migrating, changing production structure, etc.
- Migration costs affect local welfare under climate change
  - Oceania/LAC: depopulation affects innovation attractiveness
  - Africa: depopulation reduces congestion



Ratio between welfare in baseline and scenario with 25% higher migration costs.
Source: Desmet and Rossi-Hansberg (2024)

Conclusions

Conclusions

- Integrated Assessment Models
  - Integrating climate and economic systems
- Small-scale analytical IAMs
  - Simplify complexity to reach analytical conclusions and/or..
  - ..incorporating dimensions from macro/finance (e.g. uncertainty)
  - Mostly rooted in economics
- Large-scale numerical IAMs
  - Capture granular dimensions across technologies/sectors/space..
  - Integrated Assessment Models (IAMs
  - Computable General Equilibrium (CGE) models
  - Spatial IAMs