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Optimal emissions under exogenous and endogenous learning

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Introduction

Urgent need for climate mitigation

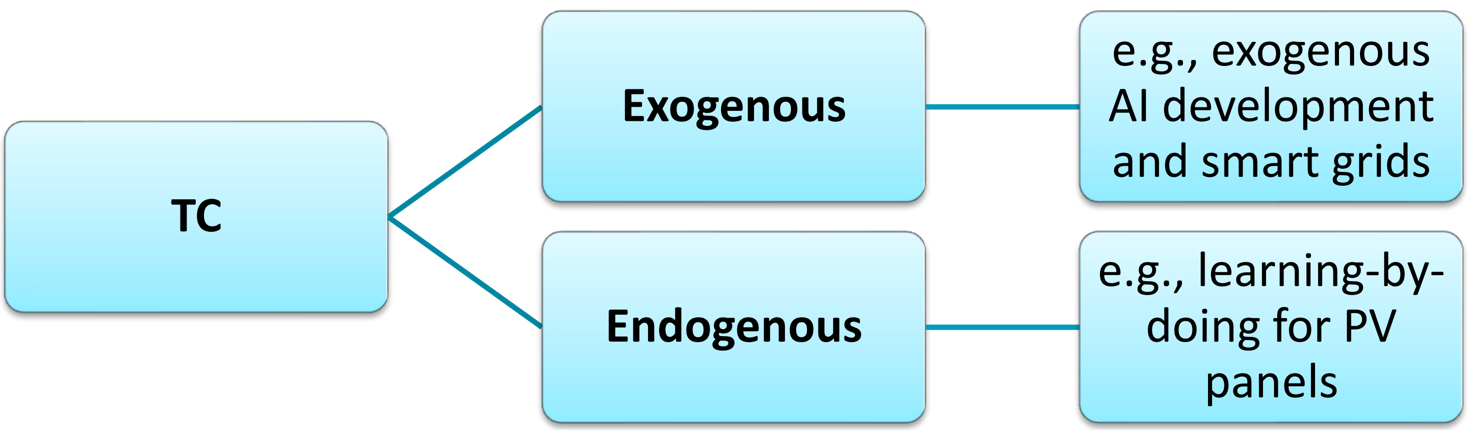
Climate policy: emissions targets, carbon prices, etc

Policy makers need guidance

Many ≠ models and scenarios (optimal emissions trajectories)

Introduction

- **Technological change (TC)** plays an important role in the transition
- Models deal with **TC** in ≠ ways
  - we established this through our own systematic survey
  - **TC** is either modelled **exogenously or endogenously** (*through R&D investments, learning by doing, price-induced learning, economies of scale, network effects*)



- Most models do not include endogenous learning :
  - Only 4 models out of 23 include endogenous **TC**

Introduction

- Our research question: what is the differentiated **impact** of endogenous and exogenous TC **on the optimal mitigation path?**
- **How ?**

1. We build on some old ideas (Goulder and Mathai, 2000; Manne and Richels, 2004 ; Popp, 2004) to create a modelling framework capable of disentangling the effects of exogenous and endogenous learning
2. Analytical, theoric results
3. We calibrate our IAM (Integrated Assessment Model) model to IPCC and NGFS database
4. We estimate numerically the learning effects

The model : maximising welfare

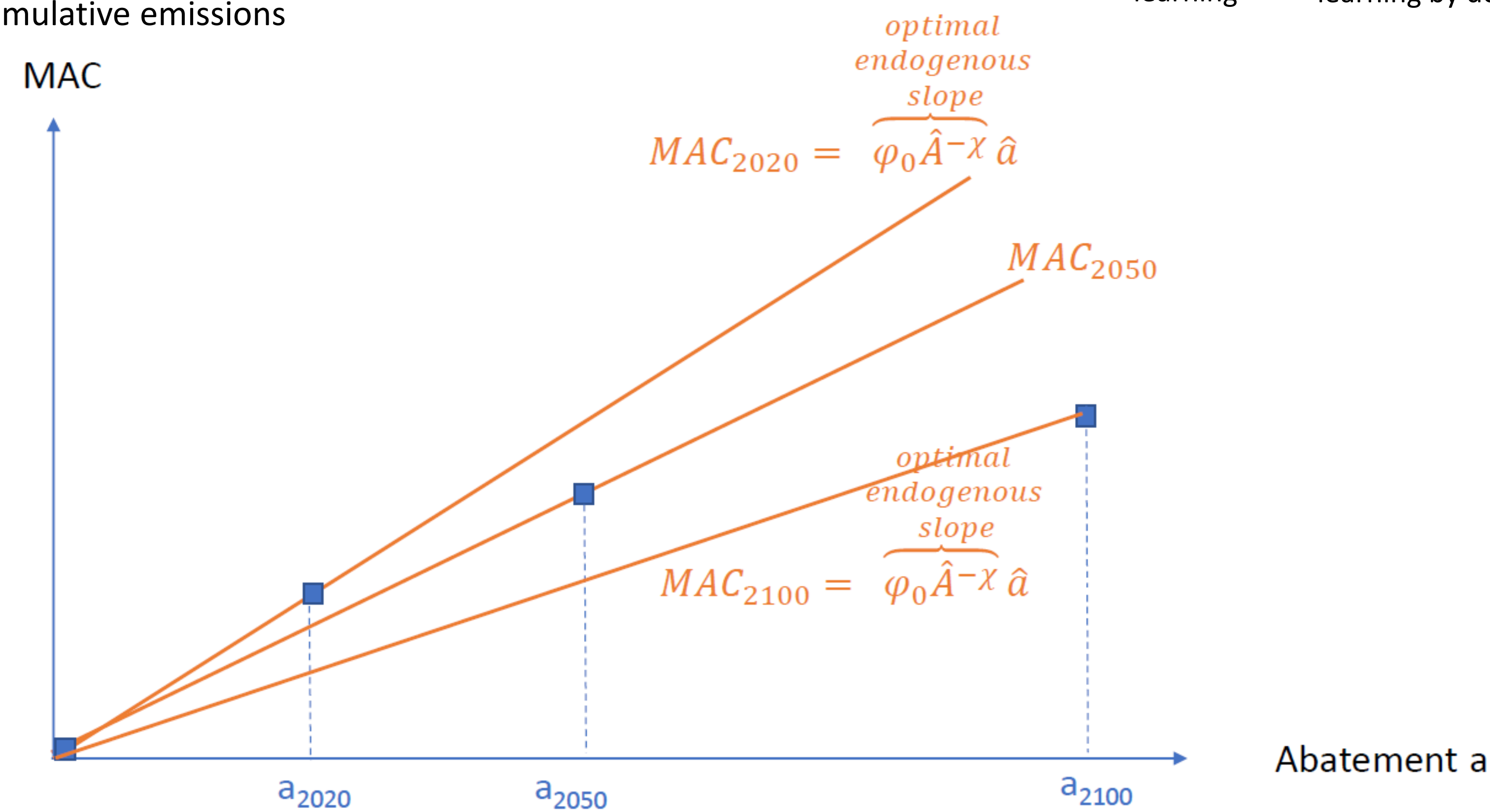
- We build a simple IAM (Integrated Assessment Model)
- The utility function is $U = \frac{c^{1-\eta}}{1-\eta}$
- The welfare function is $max \int_0^\infty e^{-(\delta-n)t} \frac{c^{(1-\eta)}}{1-\eta}$

  - With $c = c_0 e^{\left(gt \underbrace{- \frac{\varphi_t}{2} a^2 (A/A_0)^{-\chi}}_{\text{Abatement costs}} \underbrace{- \frac{\theta_2}{2} \dot{a}^2}_{\text{Inertia}} \underbrace{- \frac{\gamma}{2} \zeta^2 S^2}_{\text{Climate damages}}\right)}$
    - a, abatement
    - A, cumulative abatement
    - S, cumulative emissions

The model: our MAC function

The marginal abatement cost function is: $MAC(\%Y) = \underbrace{\varphi_t}_{\text{exogenous learning}} a \underbrace{(A/A_0)^{-\chi}}_{\text{endogenous learning by doing}}$

- a, abatement
- A, cumulative abatement
- S, cumulative emissions



The learning incentive

In a model with endogenous learning, avoiding a unit of emissions does not only give lower damages over the future path, it also decreases abatement costs of the future path. Let's call this the "***learning incentive***"

$$MAC_t = p_t = \underbrace{\int_t^{\infty} e^{-r(\tau-t)}\left(-\zeta c_T\right) d\tau}_{Social\ Cost\ of\ Carbon} + \underbrace{\int_t^{\infty} e^{-r(\tau-t)}\left(-c_S\right) d\tau}_{Social\ Gain\ of\ Learning}$$

Numerical results: calibration and scenarios

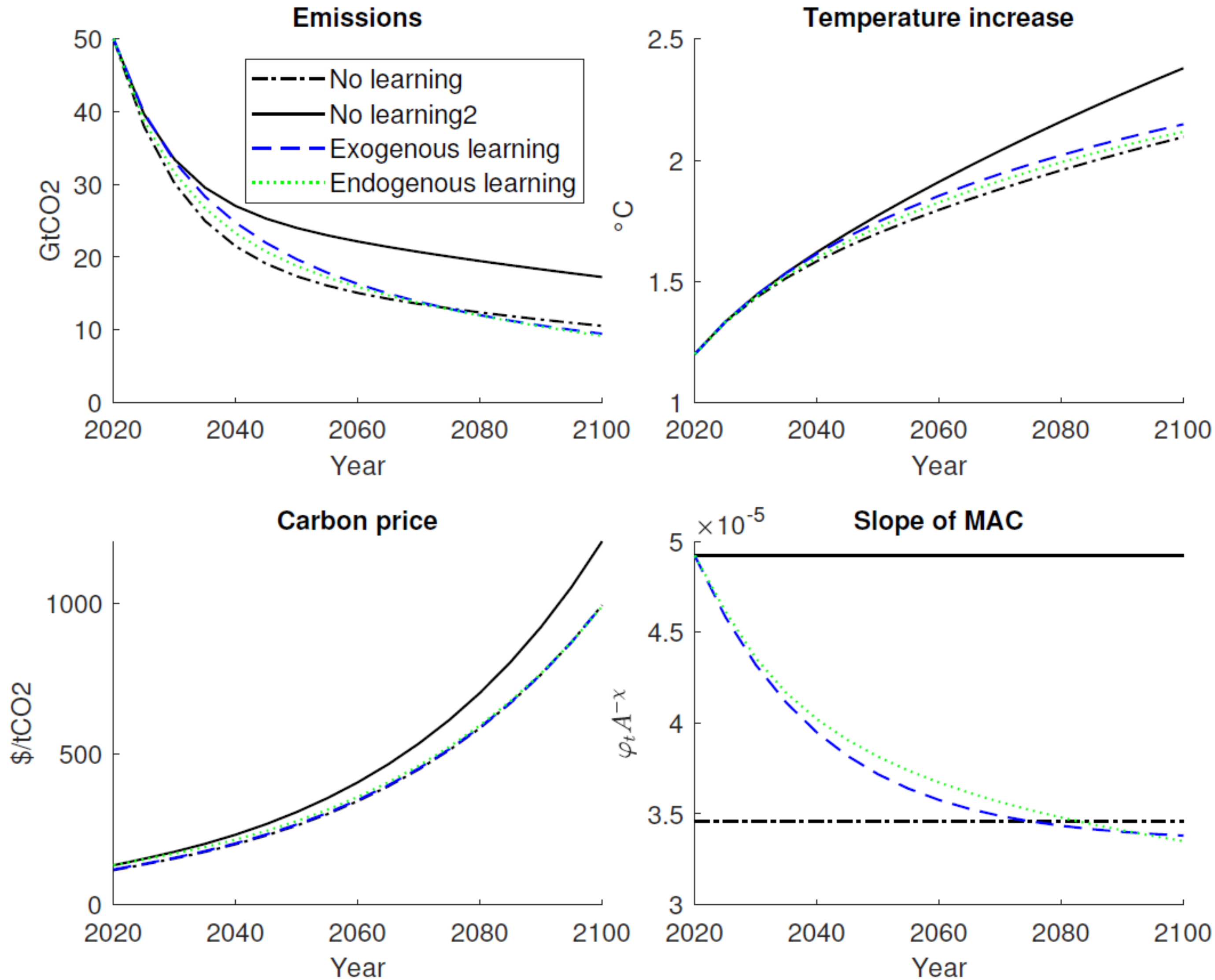
- **Calibration** of the MAC (Marginal Abatement Cost)
  - **climate scenarios database of IPCC** (1.5°C report) and NGFS
  - using maximum likelihood

- **Central scenarios**
  - No learning “1” (future costs calibration)
  - No learning “2” (current costs calibration)
  - endogenous learning
  - exogenous learning

- **Isolating the learning effects**
  - thanks to polynomials

Numerical results: central cases

- Carbon price of No learning 2 (current cost calibration) **>** Carbon price of No learning (future cost calibration)
- The slope of the MAC in the endogenous case **>** exogenous case. **But emissions are <** than in the exogenous scenario
- Including exogenous or endogenous learning **steepens** the abatement path



Methodology to isolate the learning dynamics effects

- We start with a model where there is only endogenous learning

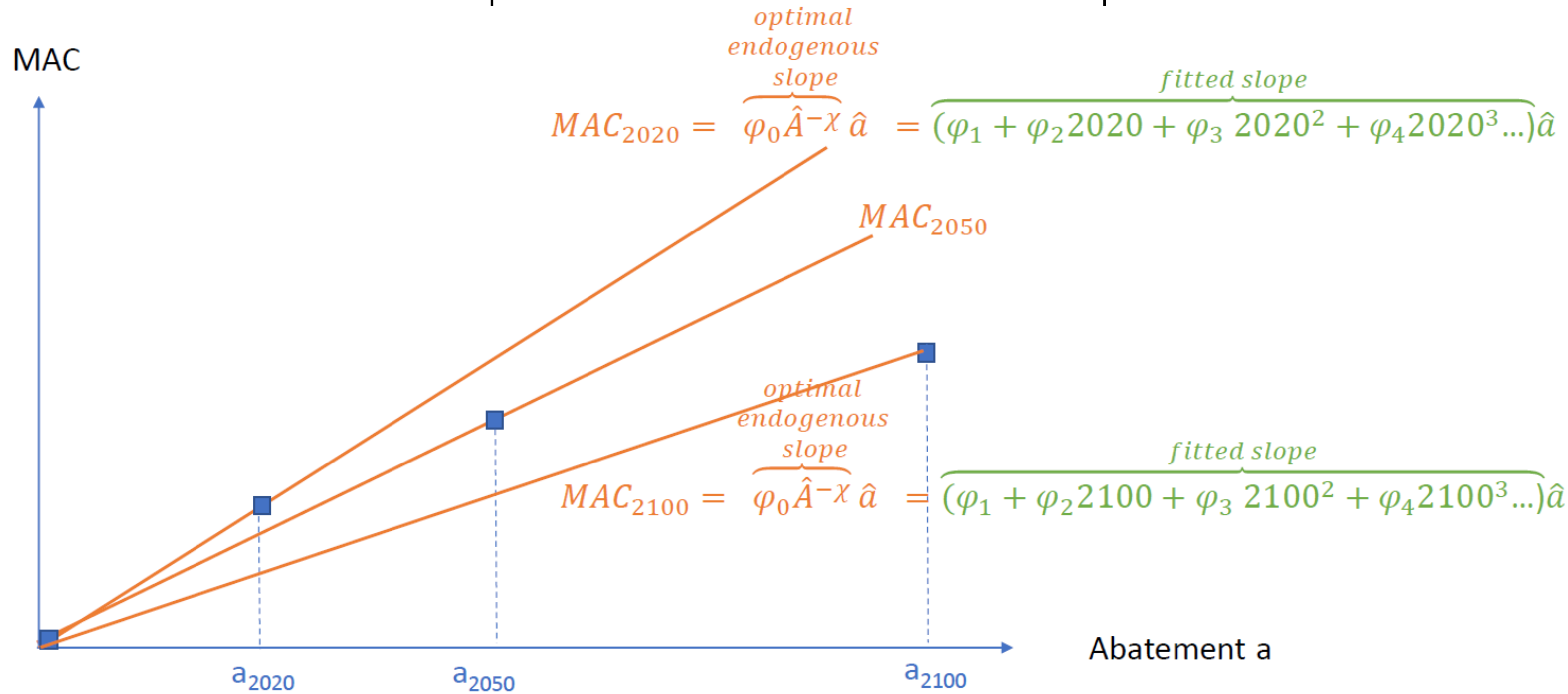
$$MAC\%(a, A) = \varphi^{endo} A^{-\chi} a$$

- We fit a twentieth-degree polynomial in time to the learning factor of the optimal endogenous learning path

$$\varphi^{endo}\hat{A}_t^{-\chi} = \sum_{n=0}^{9} \varphi_n^{exo} t^n$$

- The new marginal abatement cost, expressed as % of consumption is then

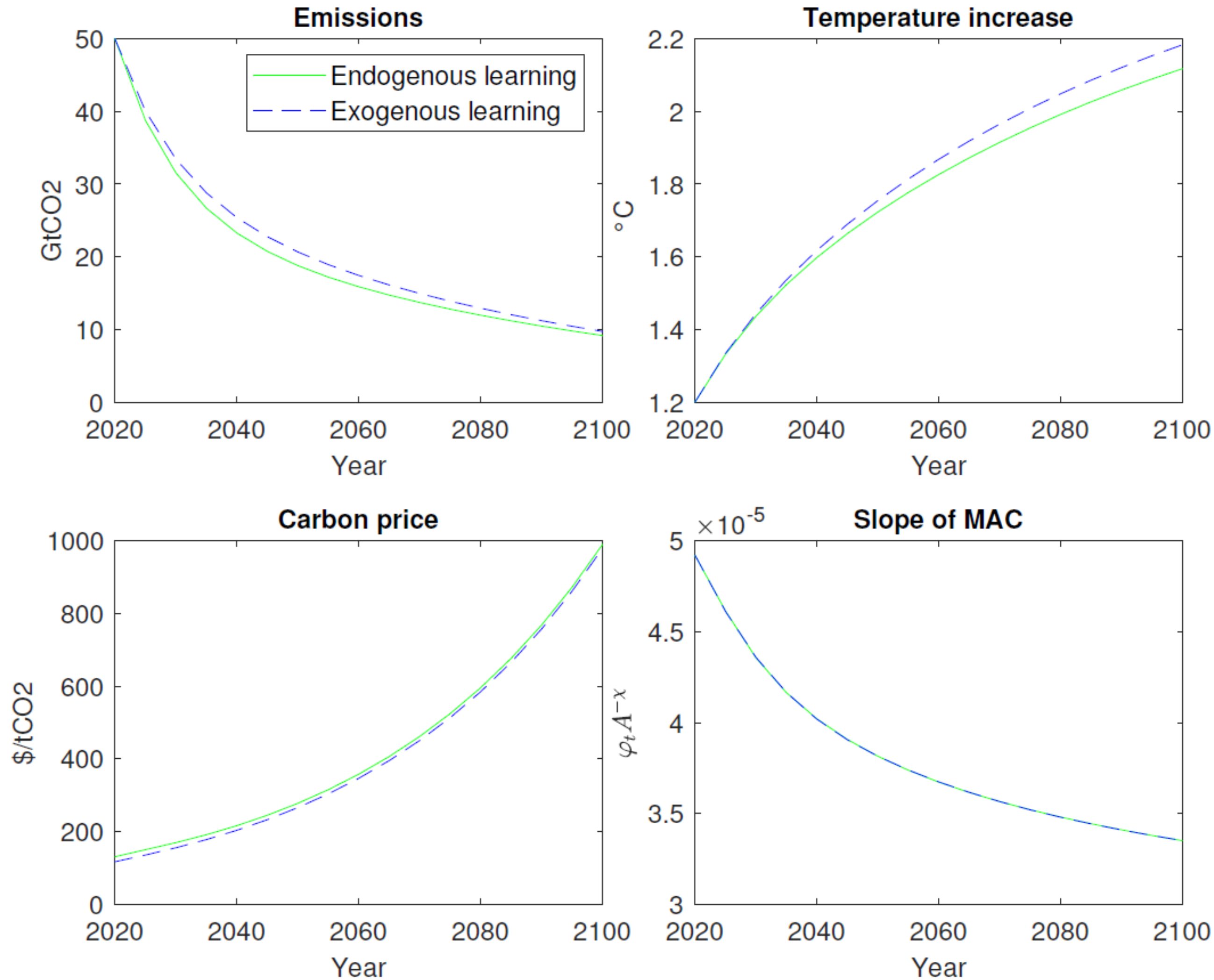
$$\hat{MAC\%} = \left(\sum_{n=0}^{9} \varphi_n^{exo} t^n\right) \hat{a}$$



Numerical results: isolating the learning effect

- Including the endogenous learning dynamic → -1.88 **GtCO2 in 2050** (**-9.11%**), -0.56 GtCO2 in 2100 (-5.78%). The **temperature is 3.01% higher** in the exogenous case in 2100 (2.184° compared to 2.118°)

- Similar analysis but no learning versus exogenous learning → **no effect of exogenous learning** on the optimal trajectory



Conclusion

- Optimal emissions trajectories produced by models → **inform policies**.
- In this paper: **differentiated impact of endogenous and exogenous TC on the optimal path**.

- **19 models out of 23** IAMs reviewed : only **exogenous TC.**
- Theoretically, **endogenous learning modifies the optimality condition →** supplementary term: the **future gains from endogenous learning**.

- Endogenous learning dynamic → **significant** effects (compared to "exogenous learning")
  - This common practice **underestimates the optimal abatement → more emissions** + higher warming at the end of the century
  - <u>Strong conclusion for policy makers and modellers</u>: trajectories coming from models without endogenous learning are not ambitious enough
- Exogenous learning dynamic → **0** effects (compared to "no learning")

Thank you for your attention!

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