Using Neural Networks to Compute Optimal Carbon Taxes in Economic Models of Climate Change

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Introduction

- Study the multi-region climate-policy model of Epp & Hillebrand (2026).
- Goal: compute the model with a neural-network-based global solution method.
- Motivation: TEI with Chebyshev methods is accurate, but multilayer perceptrons are expected to scale better in higher dimensions.

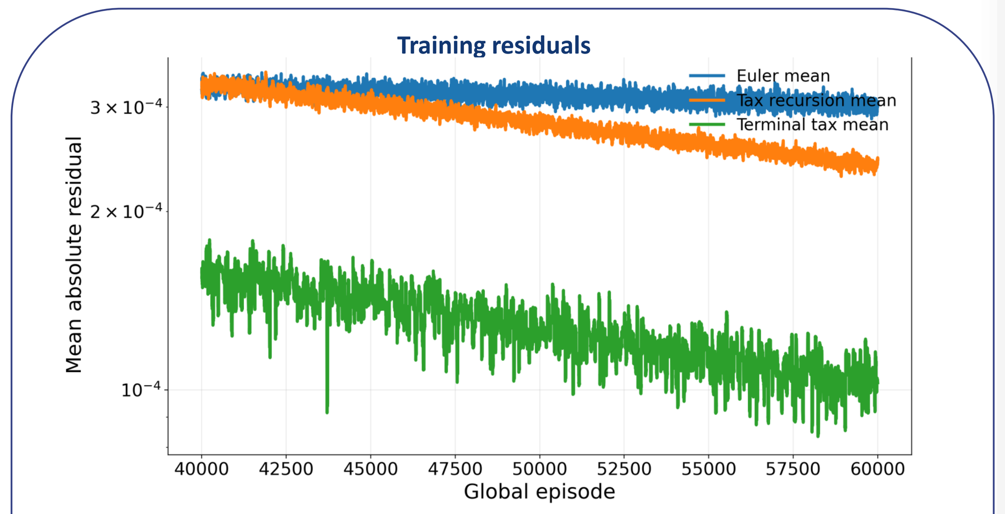
Model

- Two heterogeneous regions: resilient and vulnerable.
- Stochastic productivity and climate-damage risk.
- Endogenous emissions, temperature dynamics, and regional carbon taxes.
- Use of the Epp & Hillebrand “autarky scenario” since it has the highest dimensional state space.
- TEI solution used as the benchmark reference.

Methods

- Based on Deep Equilibrium Nets following Azinovic, Gaegauf & Scheidegger (2022).
- Train equilibrium policy functions directly on residuals; no labeled solutions required.
- Key addition: learned time embedding for transition-path variation. (Bengio et al. 2003)
- Displayed run: 32-dimensional time embedding, 60k episodes.

Results / Diagnostics



- Residual diagnostics decline strongly during training.
- Benchmarking against TEI remains essential.

Discussion

- Neural paths closely reproduce TEI transition dynamics.
- Approximation weaknesses are concentrated in late periods.
- Same-state and residual-tail diagnostics reveal where accuracy still needs improvement.

DEQN solver with 32-dimensional time-embedding

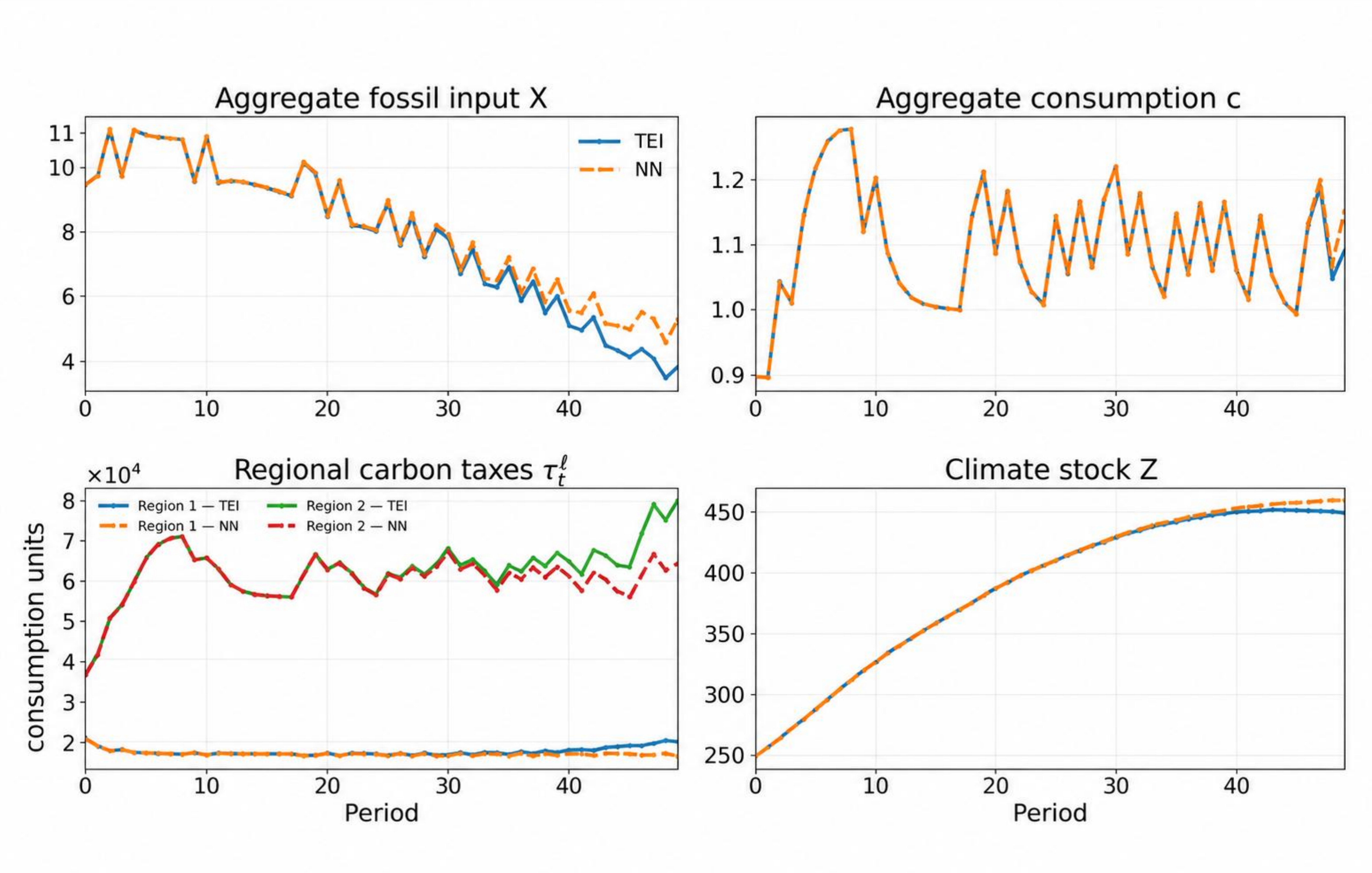
A neural-network alternative solution method for a two-region climate-policy model

Main finding: the neural solver closely tracks TEI along simulated paths while diagnostics identify where approximation quality still deteriorates.

State → MLP + time embedding → controls → equilibrium residuals → diagnostics vs TEI

Common-start simulation: neural policy vs TEI reference

Both policies start from the same initial state and are rolled forward under the same shock path.



The pathwise comparison shows very close agreement in aggregate consumption, with larger late-period deviations in fossil input, regional carbon taxes, and the climate state.

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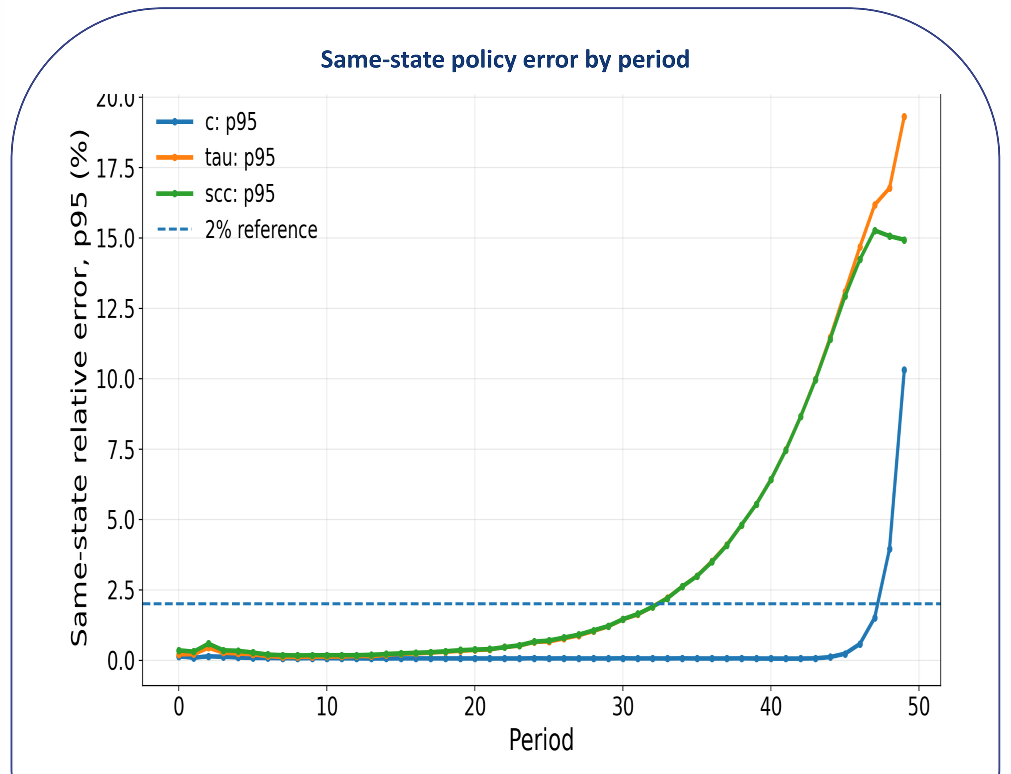
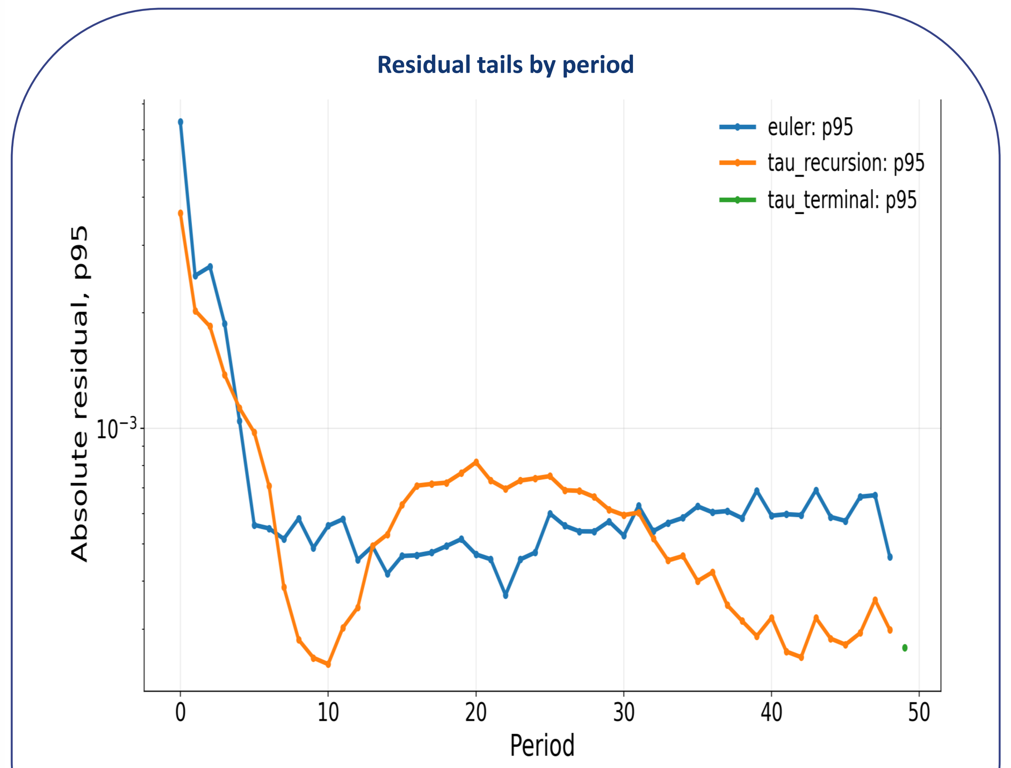
Additional info

Approximation quality





Future Extensions

- Adaptive collocation / replay: use TEI diagnostics to select hard late-period states, but train only on residuals.
- Residual-weighted replay tests whether off-path tau/SCC errors can be reduced without supervised TEI labels.
- Related literature: Brumm & Scheidegger (2017) and Nabian et al. (2021)

References

- Epp, M., & Hillebrand, M. (2026). Climate Policy and International Risk Sharing.
- Azinovic, M., Gaegauf, L., & Scheidegger, S. (2022). Deep Equilibrium Nets.
- Bengio, Y., Ducharme, R., Vincent, P., & Jauvin, C. (2003). Learned distributed representations.
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