# Optimal transition to a low-carbon economy

E. Campiglio[1,2,3] S. Dietz[3,4] F. Venmans[3,5]

*Paris School of Economics*

*Regulation and Environment Seminar*

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[1]University of Bologna

[2]RFF-CMCC European Institute on Economics and the Environment

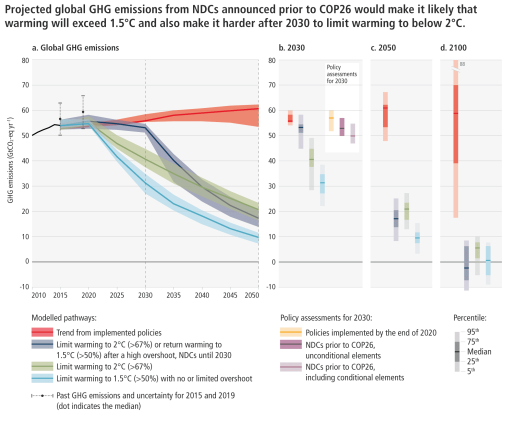
[3]London School of Economics and Political Science

[4]CESifo

[5]University of Mons

# Motivation: move to a low-carbon economy

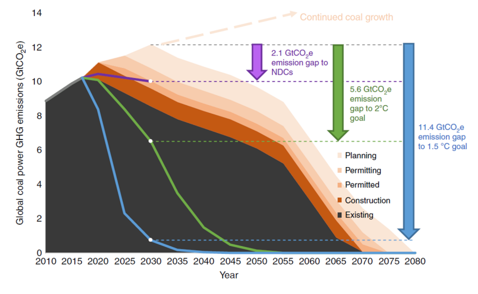
- Goal: bring GHG emissions close to zero
- What is the optimal strategy to get there?
- Three key aspects to consider

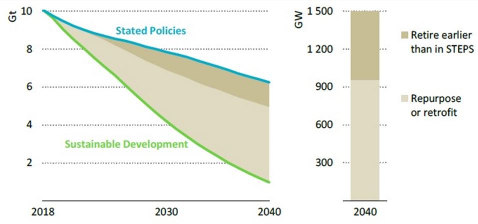



Mitigation scenarios. Source: IPCC (2022)

# 1. Capital inertia and stranding

- Capital choices are (partly) irreversible
- Rapid transition → High-carbon capital 'stranding'
- Potential wider macro-financial impacts (Semieniuk et al., 2021)

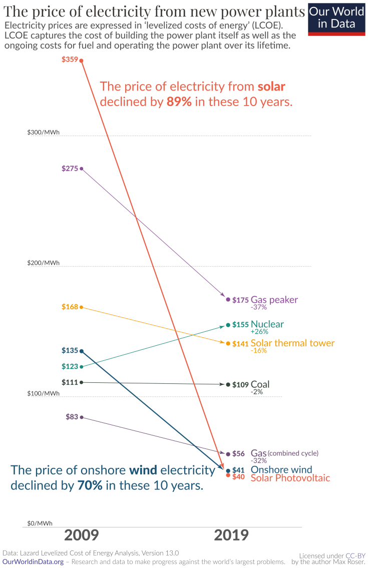



Potential coal stranding: Cui et al. (2019); IEA (2019)

# 2. Clean technological progress

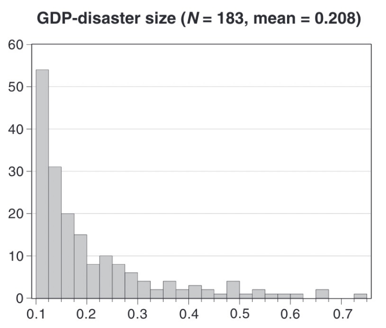
- Technology costs evolve in time
- R&D, spillovers, learning/experience, network effects etc.
- Should we wait to abate until costs are lower?

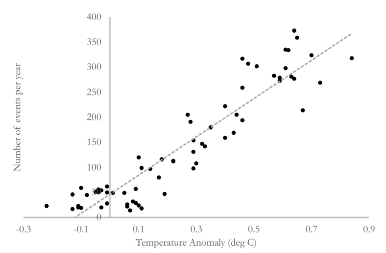



Our World in Data

# 3. Uncertainty

- Multiple sources of climate-related uncertainty (Heal and Millner, 2014)
- Gradual uncertainty
- Macroeconomic and climate-related disasters



# Three key features of our model

- Dynamic model with clean/dirty capital and climate damages
- Capital inertia and stranding
  - Investment adjustment costs on both capital stocks
  - Disinvestment adjustment costs $\rightarrow$ non-linear stranding effects
- Clean technological progress
  - Abatement costs as clean/dirty capital productivity differentials
  - Exogenous/endogenous drivers of abatement cost reduction
- Multiple sources of uncertainty
  - Brownian motions on temperature, capital stocks, productivity
  - Temperature-dependent jumps in productivity (Barro disasters)
  - Recursive preferences (Epstein and Zin, 1989; Weil, 1990)

# Connections to literature

- Adjustment costs (Gould, 1968; Lucas Jr, 1967)
  - Coulomb et al. (2019); Vogt-Schilb et al. (2018); van der Ploeg and Rezai (2020)
- High-carbon stranding
  - Capital stranding in deterministic models (Rozenberg et al., 2020; Baldwin et al., 2020; Coulomb et al., 2019)
  - Capital reconversion at a cost (Hambel et al., 2021)
- Technological progress
  - Popp (2019); Gerlagh et al. (2009); Gillingham et al. (2008)
  - Experience (Arrow, 1962; Boston Consulting Group, 1970)
- Uncertainty
  - Recursive IAMs: Lemoine and Traeger (2014); Cai and Lontzek (2019); Karydas and Xepapadeas (2019); van den Bremer and van der Ploeg (2021); Hambel et al. (2021); Olijslagers et al. (2021)

## Overview of results: benchmark transition pathway

- Benchmark optimal transition with full model
  - Carbon price: 2021: US\$123 $\rightarrow$ 2050: US\$260
  - Stop to dirty investments + US\$2.6 trillion cum. disinvestment
  - 50% GHG drop in 2020s + slower reduction after
  - Temperature just under 2°C in 2100
- Optimal price decomposition
  - Our carbon price corresponds to optimal MAC
  - Main drivers in 2021: deterministic SCC (81%); temperature disaster risk premium (17%); technological change (12%); Dirty capital contraction (-12%)
- Delayed and unexpected policies
  - $\rightarrow$ Increase in cumulative stranding

# Overview of results: disentangling impacts

- Capital inertia
  - No inertia $\rightarrow$ Massive immediate disinvestments
  - Capital inertia $\rightarrow$ Emissions/temperature inertia and higher carbon prices
- Clean technological progress
  - Falling costs lead to lower emissions/temperatures and to lower carbon prices
  - But: endogenous tech progress $\rightarrow$ carbon price premium
- Uncertainty
  - Lower emissions/temperature (precaution)
  - Higher carbon prices and larger divestment
  - Temperature-dependent disasters main driver
- Comparison to ‘straw man’ model:
  - Net carbon price premium of 17% in 2021

# Two alternative policy/planning objectives

- ‘Cost-benefit’ problem
  - Trade-off between abatement costs ($K_d \rightarrow K_c$) and climate damage costs ($E \rightarrow T \rightarrow \Omega$)
  - Maximisation of value function
- 'Cost-effectiveness’ problem
  - In line with international commitments (e.g. Paris agreement)
  - Minimisation of abatement costs
  - 1.5°C cost-effectiveness: 2021: US$167 → 2050: US$351
- 2°C cost-benefit vs 2°C cost-effectiveness
  - Ignoring climate damages → emission reduction back-loading
  - Carbon price 18% lower in 2021 in 2°C cost-effectiveness

# The model

# Production function

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

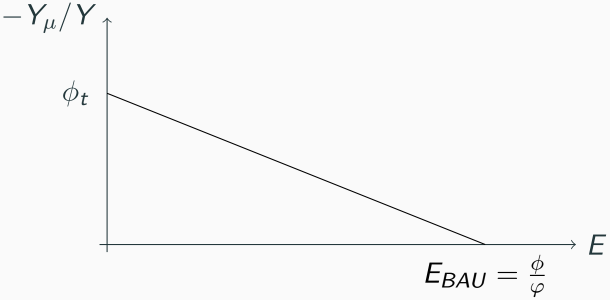
where

- $A$: TFP (subject to volatility + disasters)
- $L$: Labour growing at rate $g_L$
- $\Lambda$: Emissions abatement cost multiplier
- $\Omega$: Climate damage multiplier

## Abatement cost multiplier $\Lambda$

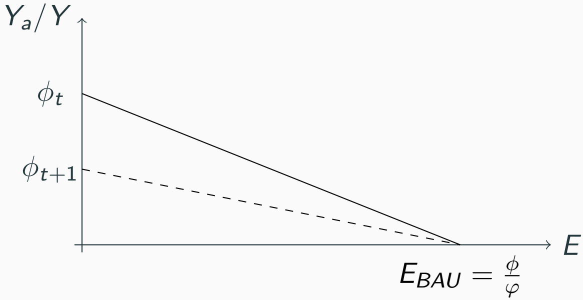
$$\Lambda = \exp\left(-\frac{\varphi_t}{2}\mu^2\right)$$

- Abatement $\mu = \phi_t/\varphi_t - E$, with $E_{BAU} = \phi_t/\varphi_t$
- $\phi$: marginal abatement cost when $E = 0$
- $\varphi$: slope of marginal abatement cost function
- Marginal abatement cost (MAC) function: $-Y_\mu/Y = -\varphi_t\mu$



# Clean technology costs fall over time

- Exogenous component
  - Spillovers from general tech progress (AI, nanotechnology, etc.)
  - Exogenous growth rates $g_\phi = g_\varphi < 0$
- Endogenous component (learning/experience)
  - MAC parameters evolve as a function of cumulative abatement $\tilde{M}$, with constant learning rate



# Abatement cost dynamics

- MAC at zero emissions evolves according to

$$\phi_t = \phi_0 \left( \omega \frac{1}{M^{\epsilon}} + (1-\omega)\,\frac{1}{1+g_{\phi}\tau} \right)$$

where $\tau$ is 'artificial' time, $\tilde{M}$ is cumulative emissions abatement and $\epsilon$ is a constant elasticity

- MAC function slope parameter evolves according to

$$\varphi_t = \varphi_0 \left( \omega \frac{1}{M^{\epsilon}} + (1-\omega)\,\frac{1}{1+g_{\varphi}\tau} \right)$$

where $g_{\phi} = g_{\varphi}$ so that $E_{BAU}$ remains fixed

# Climate damage multiplier $\Omega$

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

where

- $\gamma$: damage function coefficient
- $T = \zeta S$: global mean temperature relative to pre-industrial
- $S$: cumulative emissions
- $\zeta$ is the transient climate response to cumulative carbon emissions (TCRE)

# Dirty and clean capital stocks

$$K = K_d + K_c$$

- Not perfect substitutes!
  - Equally productive only at $E_{BAU}$; elsewhere $Y_{Kd} > Y_{Kc}$
  - $+$ investment/disinvestment costs
  - $\rightarrow$ Replacing dirty with clean capital comes at a cost
  - We assume $K_c > K_d$ ($K_d$ concentrated in upstream sectors)
- Use of $K_d$ produces emissions $E$ at intensity $\psi_t$

$$E = \psi_t K_d$$

where $\psi$ decreases exogenously at rate $g_\psi$

# Investment/disinvestment adjustment costs

- Convex adjustment costs on both dirty/clean investments

$$\iota_j = \frac{\chi_j i_j^2}{k}$$

where $i$ is investments and $\chi_j$ the adjustment cost parameters

- If $i_d = 0$ emissions decrease at rate $\delta_d + g_\psi$
    - But optimal $i_d$ can be negative!
- Convex disinvestment costs ($r \equiv i_d$ iff $i_d < 0$),

$$\kappa(r) = \frac{\theta_1 r^{\theta_2}}{k}$$

$\rightarrow$ When dirty assets are decommissioned/repurposed, less than 100% of their value can be recovered ('stranding')

# Sources of uncertainty (i)

- Temperature response to emissions
    - Brownian motion $W_T$
    - $\sigma_T = 0.03$ calibrated to IPCC models $T$ range in 2100

$$\mathrm{d}T = \zeta E \mathrm{d}t + \sigma_T T \mathrm{d}W_T$$

- Value of capital stocks
    - Brownian motions $W_d$ and $W_c$ with correlation coefficient $\rho_k$
    - $\sigma_j = 0.01 \to 5\%$ chance of a shock larger than 2% of GDP

$$\mathrm{d}k_j = \left( i_j - \frac{\chi_j i_j^2}{k} - (\delta_j + g_L + g) k_j \right) \mathrm{d}t + \sigma_j k_j \mathrm{d}W_j$$

# Sources of uncertainty (ii)

- Productivity/growth prospects
  - Brownian motion $W_A$
  - Poisson process $P$

$$\mathrm{d}\tilde{A} = \left(g_{A1}\tilde{A} + (\tilde{A}_0 - \tilde{A})g_{A2}\right)\mathrm{d}t + \sigma_A \tilde{A}\mathrm{d}W_A - \xi_1(1+\xi_2 T)\tilde{A}\mathrm{d}P$$

where

- First term governs drift TFP to a steady state
- $\xi_1 = 0.2$: Size of macro-economic shock without climate change (20% GDP loss with 1.7% probability)
- $\xi_2 = 0.07$: Effect of temperature on macro shock size (macro jump 20% $\rightarrow$ 21.4% when $T = 2^\circ C$)

## Consumption and utility

- Consumption

$$c = y - i_d - i_c - \kappa(r)$$

- Epstein-Zin-Weil preferences Details

$$V(k_d, k_c, S, \tilde{A}, t) = \max_{i_c, i_d} \mathbb{E} \int_0^\infty -f(k_d, k_c, S, \tilde{A}, t, V, i_d, i_c) d\tau$$

  - Value function $V$ of expected welfare
  - $RRA = 4 > EIS = 1.35 \rightarrow$ Preference for early resolution of uncertainty

- HJB equation

$$\max_{i_c, i_d} \left\{ f + \frac{1}{\mathrm{d}t} \mathbb{E}[dV(k_d, k_c, S, \tilde{A}, t)] \right\} = 0$$

# Calibration

# Calibration strategy

- Time:
  - One-year time steps
  - $g_\tau = g + g_L - g_\psi = 0.015$
  - Starting time period: 2020
- Three main strategies to calibrate our parameters
  - Standard values in the literature or recent empirical estimates
  - Calibration to replicate empirical evidence or desired features of starting values
  - Estimation by fitting our model to energy systems model database Details

# Preferences and production

| Parameter | Symbol | Value | Source |
|---|---|---|---|
| Elasticity of marginal utility of consumption | $\eta$ | 1.35 | Drupp et al. (2018) |
| Relative risk aversion | $RRA$ | 4 | Barro (2009) |
| Discount rate | $\rho$ | 0.011 | Drupp et al. (2018) |

| Parameter | Symbol | Value | Source |
|---|---|---|---|
| Initial TFP value | $A_0$ | 3.44 | Calibration |
| Trend TFP growth rate | $g$ | 0.0237 | Calibration |
| Std Dev of TFP Brownian motion | $\sigma_A$ | 0.01 | Barro (2009) |
| Initial population | $L_0$ | 7.794 | UN (2019) |
| Population growth rate | $g_L$ | 0.0042 | UN (2019) |
| Output elasticity of capital | $\alpha$ | 0.3 | Standard |
| Initial dirty capital | $K_{d,0}$ | 28 | Calibration |
| Initial clean capital | $K_{c,0}$ | 320 | Calibration |
| Depreciation rate | $\delta_d, \delta_c$ | 0.04 | Calibration |
| Initial carbon intensity | $\psi_0$ | 2 | Calibration |
| $\psi$ decline rate | $g_\psi$ | 0.01 | Calibration |
| Adjustment cost parameter | $\chi_d, \chi_c$ | 0.1 | van der Ploeg and Rezai (2020) |
| Std Dev of $k_d$ and $k_c$ Brownian motions | $\sigma_d, \sigma_c$ | 0.01 | Barro (2009) |
| Correlation between $k_d$ and $k_c$ Brownian motions | $\rho_k$ | 0.5 | By assumption |
| Size of macro disasters without climate | $\xi_1$ | 0.2 | Calibration |

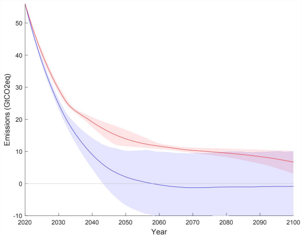
# Climate and emission abatement

| Parameter | Symbol | Value | Source |
|---|---|---|---|
| Temperature increase in 2020 | $T_0$ | 1.2°C | IPCC (2021) |
| TCRE | $\zeta$ | 0.0006 | IPCC (2021) |
| Climate damage function parameter | $\gamma$ | 0.0077 | Howard and Sterner (2017) |
| Std Dev of $T$ Brownian motion | $\sigma_T$ | 0.03 | IPCC (2021) |
| Dependence of macro disasters on $T$ | $\xi_2$ | 0.07 | Calibration |

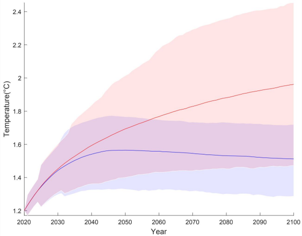
| Parameter | Symbol | Value | Source |
|---|---|---|---|
| $\phi$ initial value | $\phi_0$ | 0.00252 | Calibration |
| $\phi$ decline rate | $g_\phi$ | 0.69 | Calibration |
| $\varphi$ initial value | $\varphi_0$ | 0.000042 | Estimation |
| $\varphi$ decline rate | $g_\varphi$ | 0.69 | Estimation |
| Disinvestment cost function parameter | $\theta_1$ | 705 | Estimation |
| Disinvestment cost function exponent | $\theta_2$ | 2.1 | By assumption |
| Exogenous learning weight parameter | $\omega$ | 0.5 | Calibration |
| Cumulative abatement at $t_0$ | $\tilde{M}_0$ | 100 | UNEP (2021) |
| Elasticity of MAC to cumulative emissions | $\epsilon$ | 0.1 | Estimation |

# Numerical results

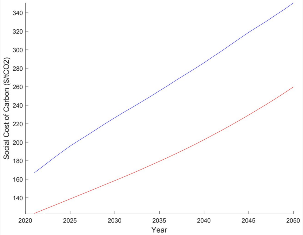
# The benchmark optimal transition



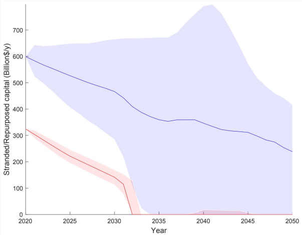

**(a)** Emissions $E$




**(b)** Temperature $T$



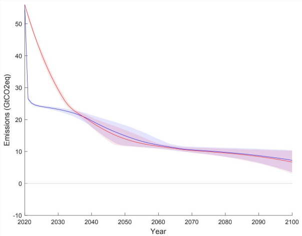

**(c)** Carbon price $p$




**(d)** Dirty capital disinvestment $R$

Red: cost-benefit. Blue: 1.5°C cost-effectiveness.

# The impact of capital inertia

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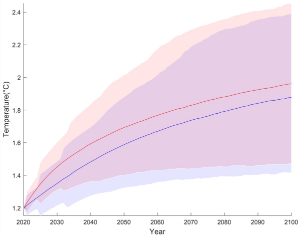


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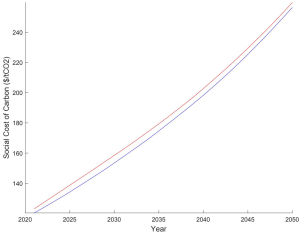


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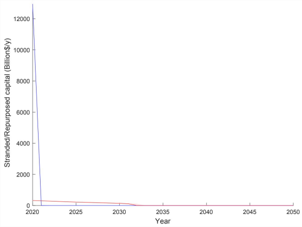
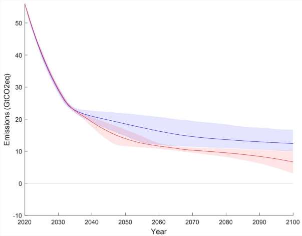



**(d)** Dirty capital disinvestment $R$

Red: cost-benefit. Blue: without adjustment/disinvestment costs ($\chi_c = \chi_d = \theta_1 = 0$)

# The impact of learning

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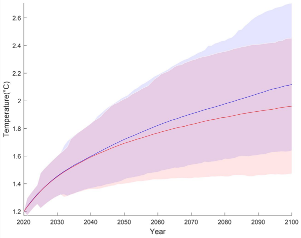


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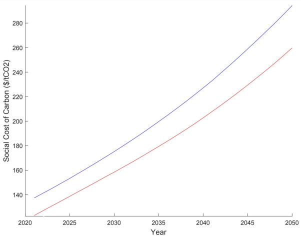
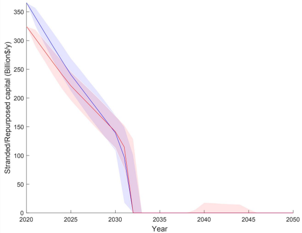


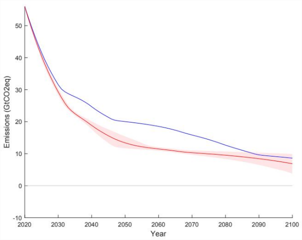

**(c)** Carbon price $p$




**(d)** Dirty capital disinvestment $R$

Red: cost-benefit. Blue: without learning ($\phi_t = \phi_0$ and $\phi_t = \phi_0 \; \forall t$)

# The impact of uncertainty

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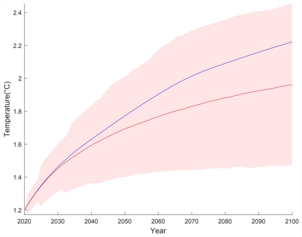


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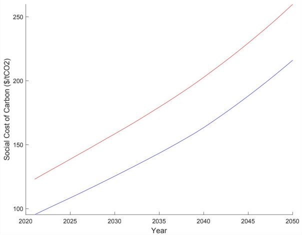


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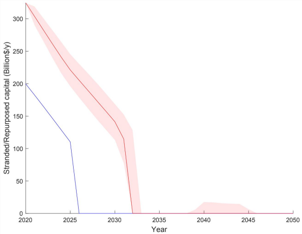
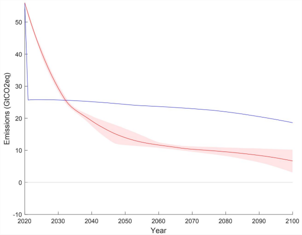



**(d)** Dirty capital disinvestment $R$

Red: cost-benefit. Blue: without uncertainty $(\sigma_T = \sigma_j = \sigma_A = \xi_1 = 0)$

# Comparison with ‘straw man’ model

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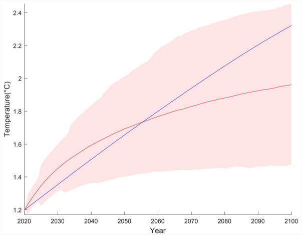


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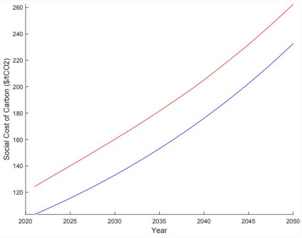
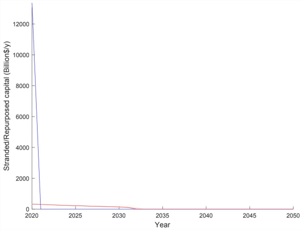



**(c)** Carbon price $p$




**(d)** Dirty capital disinvestment $R$

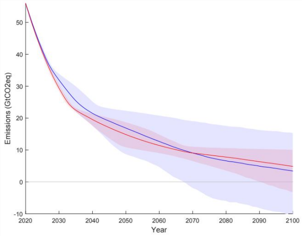
Red: cost-benefit. Blue: without inertia, learning and uncertainty

# Summary of effects

| | Cumulative emissions 2020-2100 | Temperature in 2100 | $CO_2$ price in 2021 | Cumulative dirty capital disinvestment 2020-2050 |
|---|---|---|---|---|
| No inertia | -10.6% | -0.08°C | -2.2% | n/a |
| No learning | 19.7% | 0.16°C | 11.6% | 7.5% |
| No uncertainty | 27.7% | 0.26°C | -22.5% | -64.4% |
| Straw man | 43.2% | 0.36°C | -14.5% | n/a |

Summary of effects, relative to the full model

# Cost-benefit versus cost-effectiveness

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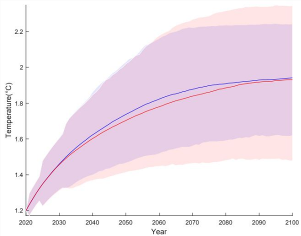


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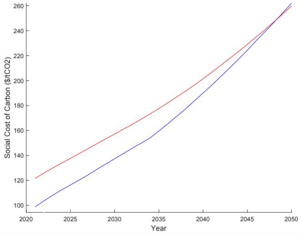


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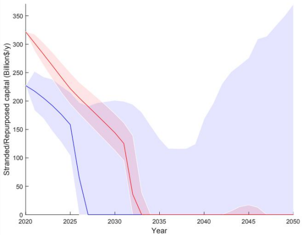



**(d)** Dirty capital disinvestment $R$

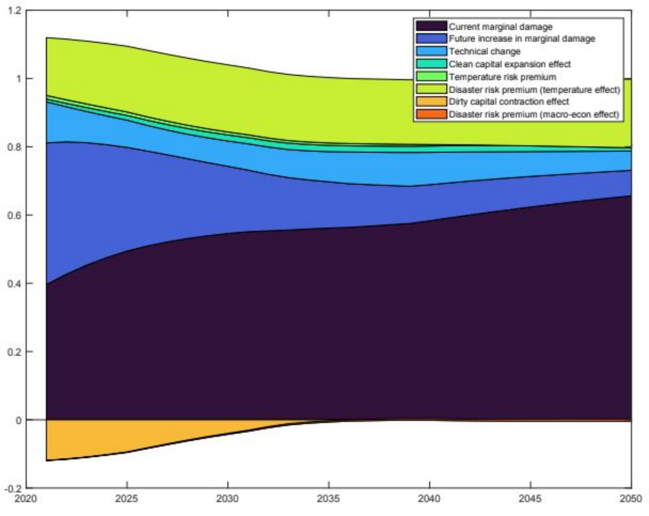
Red: 2°C cost-benefit. Blue: 2°C cost-effectiveness

# Optimal carbon price decomposition

- Analytical expression for the optimal carbon price

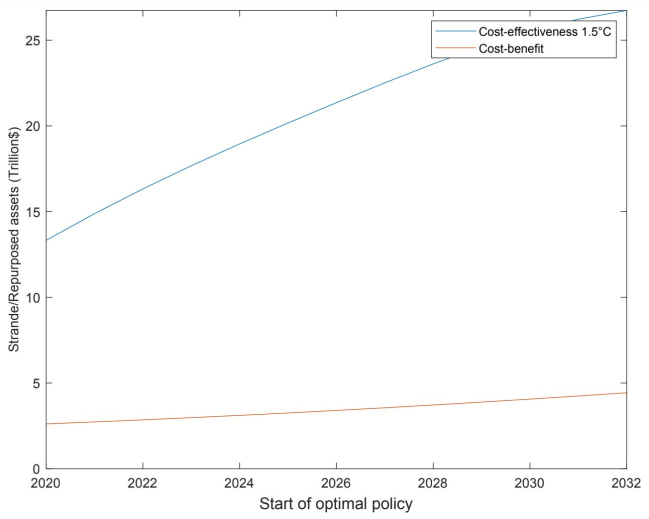
$$
\begin{aligned}
p = \quad & \Phi\{\Psi c^{-\eta} y \gamma S - V_{SS} E && \text{marginal damage cost} \\
& + \Psi c^{-\eta} y \left[ \tfrac{\varphi}{2} \mu^2 (1-\omega) \tfrac{\epsilon}{M^{\epsilon+1}} \right] - V_{tS} && \text{technological change effect} \\
& - V_{Sk_d} \left[ i_d - \chi_d i_d^2 - (\delta_d + g_L + g) k_d \right] && \text{dirty capital contraction effect} \\
& - V_{Sk_c} \left[ i_c - \chi_c i_c^2 - (\delta_c + g_L + g) k_c \right] && \text{clean capital expansion effect} \\
& - V_{SS} S \sigma_S^2 - 1/2 V_{SSS} S^2 \sigma_S^2 && \text{temperature risk premium} \\
& - 1/2 V_{Sk_d k_d} k_d^2 \sigma_d^2 - 1/2 V_{Sk_c k_c} k_c^2 \sigma_c^2 - V_{Sk_c k_d} k_d k_c \rho^k \sigma_c \sigma_d && \text{capital risk premiums} \\
& - 1/2 V_{SAA} \tilde{A}^2 \sigma_A^2 && \text{TFP volatility risk premium} \\
& - \lambda_A \left[ V_S(\tilde{A} - \Delta\tilde{A}) - V_S(\tilde{A}) \right] && \text{disaster risk} \\
& + \lambda_A V_A(\tilde{A} - \Delta\tilde{A}) \xi_1 \xi_2 \zeta \tilde{A} - V_{SA} \left( \tilde{A} g_{A1} + \left( A_0 - \tilde{A} \right) g_{A2} \right) \}, && \text{premium}
\end{aligned}
$$

# Optimal carbon price decomposition results




Y-axis is scaled in percent of the absolute price

# Policy delays increase stranding costs




Red: cost-benefit. Blue: 1.5°C cost-effectiveness

# Conclusions

# Conclusions

- We develop a recursive IAM with
  - Investment/disinvestment adjustment costs
  - Exogenous/endogenous clean technological progress
  - Multiple sources of uncertainty
- Main findings
  - Optimal transition is fast, requiring a high carbon price and active stranding of dirty assets
  - This is especially true if policies are delayed and unanticipated
  - Considering capital inertia, clean techn progress and uncertainty $\rightarrow$ net premium of 17% on the optimal carbon price today
  - Cost-effectiveness problems underestimate optimal carbon price

# Support slides

# Value function

$$V(k_d, k_c, S, \tilde{A}, t) = \max_{i_c, i_d} \mathbb{E} \int_0^\infty -f(k_d, k_c, S, \tilde{A}, t, V, i_d, i_c) d\tau$$

with

$$f(k_d, k_c, S, \tilde{A}, t, V, i_d, i_c) = \frac{c^{1-\eta}}{1-\eta} \Upsilon - \hat{\rho} V \frac{1 - RRA}{1-\eta}$$

$$\Upsilon = \hat{\rho} \left( (1 - RRA) \, V \right)^{\frac{\eta - RRA}{1 - RRA}}$$

and

$$\hat{\rho} = \rho - g_L + (\eta - 1) g$$

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# Abatement cost estimation

- Database of IAMs and energy system models
  - IPCC Special Report on 1.5°C (122 scenarios)
  - NGFS database (12 scenarios)
  - $\rightarrow$ Calculate total and marginal abatement costs
- We choose values of $\varphi_0$, $\theta_1$, $g_\varphi$ and $\epsilon$ that maximise the fit of our model, using:

$$\frac{Y}{Y_{BAU}} = \exp\left[-\frac{\varphi_t}{2}\left(E - \frac{\phi_t}{\varphi_t}\right)^2\right] - \theta_1 r^{\theta_2} \frac{L_0 e^{(g+g_L)t}}{k^* Y_{BAU}}$$

$$-Y_\mu = Y\left(\phi_t - \varphi_t E\right)$$

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# Abatement cost estimation results

| | Fixed technology costs | Exogenous technology cost decreases | Endogenous technology cost decreases |
|---|---|---|---|
| $\varphi_0$ | 3.1e-05*** | 4.2e-05*** | 4.2e-05*** |
| $\theta_1$ | 9.4e+02** | 7.0e+02** | 7.1e+02** |
| $g_\varphi$ | | 0.74*** | |
| $\epsilon$ | | | 0.10*** |
| | | | |
| N | 1605 | 1605 | 1605 |
| Log likelihood | 6654 | 6664 | 6660 |
| BIC | -13293 | -13305 | -13297 |
| AIC | -13304 | -13321 | -13313 |

* p¡.1; ** p¡.05; *** p¡.01

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# Differences in optimal carbon price shares

Differences in the share of the optimal carbon price attributable to each element, relative to the full model. Units are percentage points.

| | No capital inertia | Fixed clean tech. costs | No uncertainty | Straw man |
|---|---|---|---|---|
| | | *2021* | | |
| Current marginal damage | -0.3 | 0.0 | 9.8 | 9.3 |
| Future increase marginal damage | -24.2 | -0.1 | 14.0 | -18.2 |
| Endogenous tech. change effect | 18.9 | 0.1 | 0.3 | 25.4 |
| Clean capital expansion effect | 0.2 | 0.0 | 0.3 | 0.6 |
| Dirty capital contraction effect | 5.3 | 0.0 | -3.0 | 4.4 |
| Disaster risk premium | 0.1 | 0.0 | -22.1 | -22.1 |
| | | *2050* | | |
| Current marginal damage | -1.5 | -1.2 | 12.4 | 10.8 |
| Future increase marginal damage | 1.4 | 3.5 | 11.5 | 14.1 |
| Endogenous tech. change effect | -0.7 | -0.8 | -0.6 | -1.4 |
| Clean capital expansion effect | 0.0 | -0.1 | 0.3 | 0.6 |
| Dirty capital contraction effect | -0.3 | -0.6 | -2.0 | -2.4 |
| Disaster risk premium | 1.0 | -0.8 | -22.3 | -22.3 |

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