Market Power, Innovation, and the Green Transition

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25 September 2024 – FINPRO

Introduction

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- Some firms rely more on fossil fuels than others (lock-in)
- Winners and losers within industries

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How does market power affect the transition from a dirty to a clean economy?

Contribution and results

Contribution to the literature:

- Empirical evidence on market power and the direction of innovation: cannot be explained by current theories
- A theoretical model that incorporates empirical findings and explores the relevance for climate policy

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Preview of findings:

- Data: market leaders are, on average, more invested in dirty technologies than their direct competitors
- Theory: climate policy can lead to a strategic increase in dirty innovation by some firms because of the "escape competition effect"
- Calibration: ambitious climate policy leads to a (mostly clean) research boom and lower aggregate markups along the green transition

Literature

- Directed technical change and the environment
  - Theory: direction of innovation responds to relative prices, market sizes, and stocks of knowledge (path dependence)

    Smulders and de Nooij (2003); Acemoglu et al. (2012, 2016), Aghion et al. (2024)
  - Empirics: DTC mechanisms and policies affect innovation

    Jaffe and Palmer (1997); Newell et al. (1999); Popp (2002); Linn (2008); Noailly and Smeets (2015); Aghion et al. (2016); Calel and Dechezleprêtre (2016); Rozendaal and Vollebergh (2024)
  - Porter hypothesis: environmental regulation and competitiveness

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    Porter (1990); Porter and van der Linde (1995)
- Market power and innovation
  - Growth through creative destruction: technology ladders

    Schumpeter (1942); Aghion and Howitt (1992); Grossman and Helpman (1991)
  - Competition $\Longleftrightarrow$ innovation; strategic interaction

    Blundell et al. (1995); Aghion et al. (2005); Akcigit and Ates (2023)

Motivating evidence

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Establish the following facts:

1. The direction of innovation is path dependent
2. Market power and path dependence are correlated within industries

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Evidence suggests that market leaders are more invested in dirty technologies than their competitors

- More difficult to make them switch to clean

Data from Orbis IP and Historical

- 130 million patent applications; 1.4 million inventions
- Classified as clean, dirty, neutral following Jee and Srivastav (2023)
- Mostly energy, manufacturing, transport technologies
- Link between firms' patents and balance sheets

Data | Shares clean dirty | Totals clean dirty | Types of clean technologies | Types of dirty technologies | Gray as a share of dirty | Patents by applicant country | Patents by applicant sector

Path dependence in innovation

Knowledge stocks: $K_{it}^{T} = P_{it}^{T} + (1-\delta)K_{it-1}^{T}$, with $T \in \{C, D\}$

Innovation $\text{gap}_{it} = \sinh^{-1}(P_{it}^{C}) - \sinh^{-1}(P_{it}^{D})$

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The direction of innovation is path dependent:

- Clean patenting depends positively on K^C and negatively on K^D
  Regression table
- Vice versa for dirty patenting
- In line with the literature

Which firms are most invested in dirty technologies?

I define:

- Leaders: top 10 firms in terms of revenue in country-sector-year
- Laggards: firms in ranks 11-20

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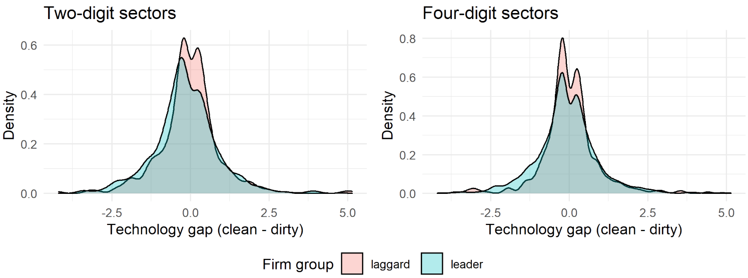

Figure: Distribution of the technology gap for leaders and laggards in 2018

Which firms are most invested in dirty technologies?

Within a country-industry-year, technology gap correlates negatively with:

- Firm size, profitability and age Regression table
- Being a market leader Regression table

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Suggests that:

- Large firms need a stronger incentive to switch to clean than smaller firms
- Climate policy can affect market power

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- Large firms need a stronger incentive to switch to clean than smaller firms
- Climate policy can affect market power

Cannot be explained by the current literature, so let's incorporate these findings in a model

- What does this mean for climate policy?

Model overview

Continuous time endogenous growth model:

- Representative consumer
- Final good consists of a continuum of intermediates
- Exponential-quadratic damages from climate change (Nordhaus and Moffat, 2017)
- Temperature linear in historical emissions (Dietz and Venmans, 2019)

Details

Model overview

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Details

Each intermediate input sector has:

- Two firms that compete on prices (limit pricing) (Akcigit and Ates, 2023)
- Good produced using either a clean or a dirty technology
- Stepwise innovation in clean and dirty
- Knowledge diffusion

Production Innovation Technology gaps Static decision Dynamic decision

Technology gaps

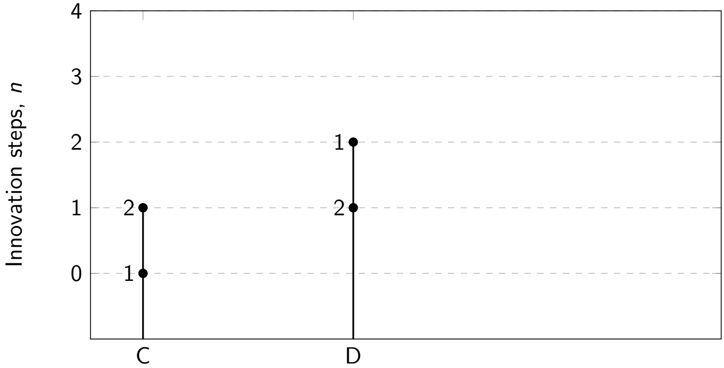
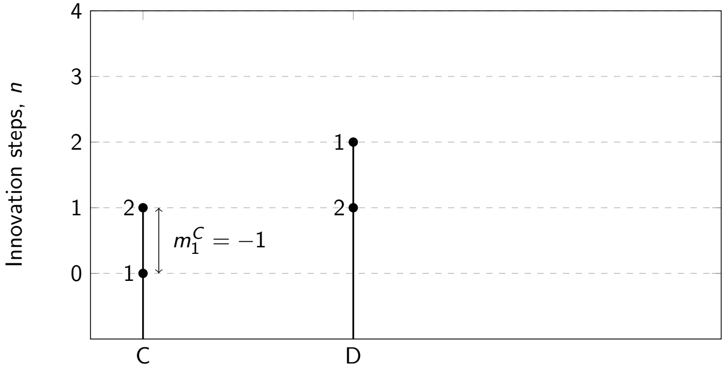


Figure: Own, clean and dirty technology gaps

Technology gaps



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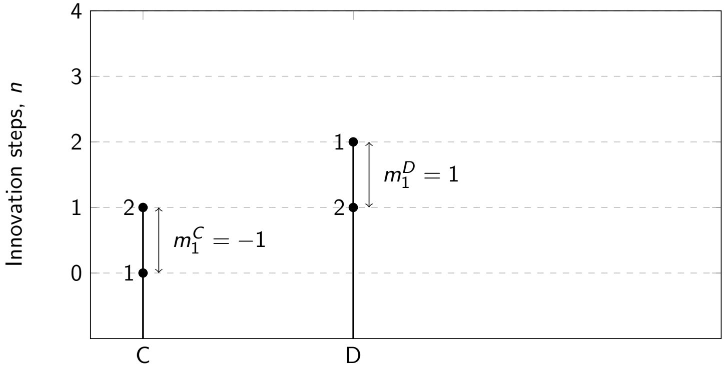

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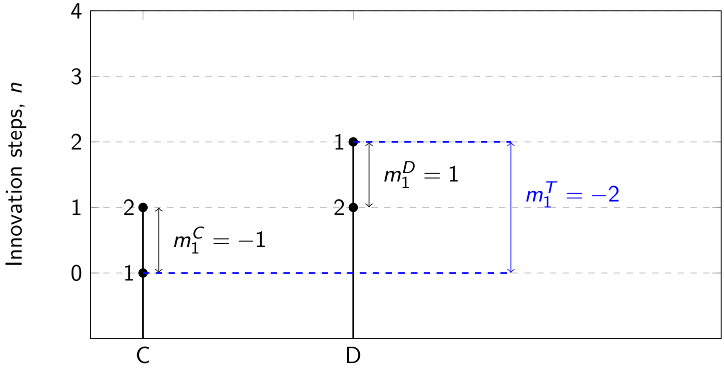

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The effect of a tax

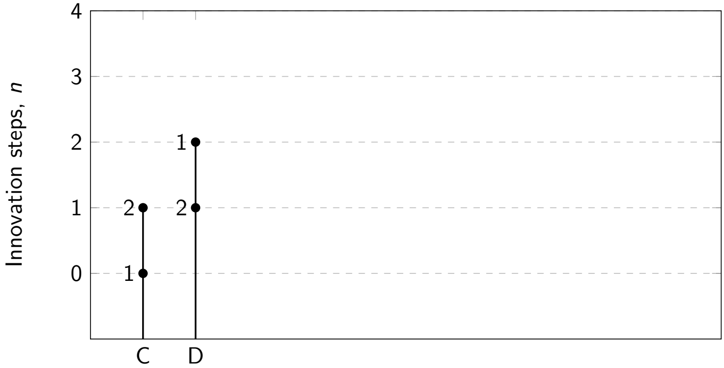
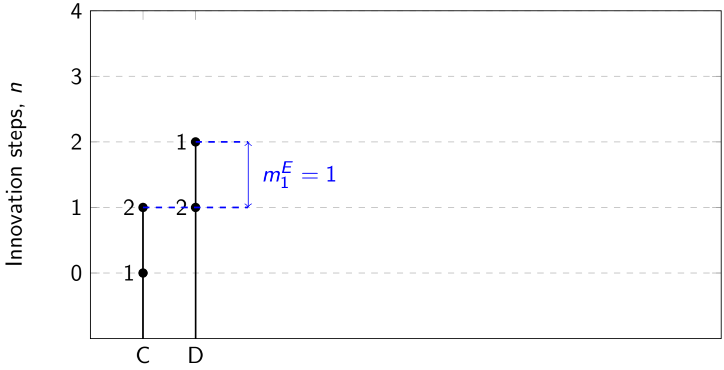


Figure: A carbon tax affects the effective technology gap

The effect of a tax



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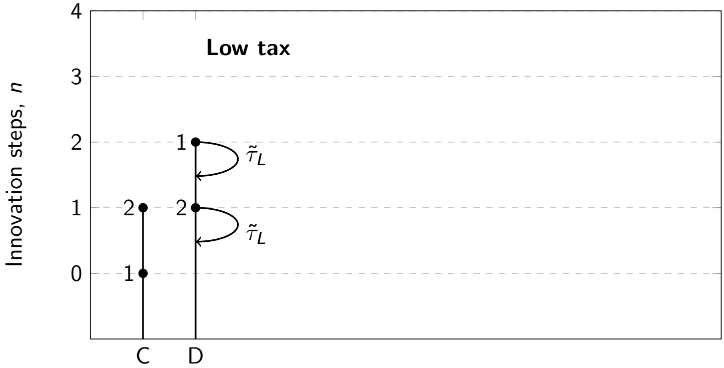

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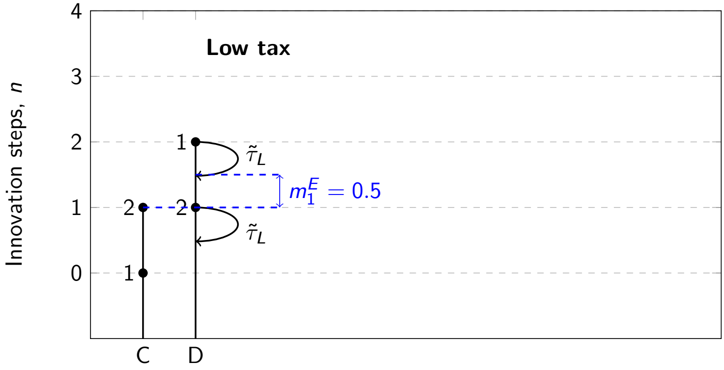

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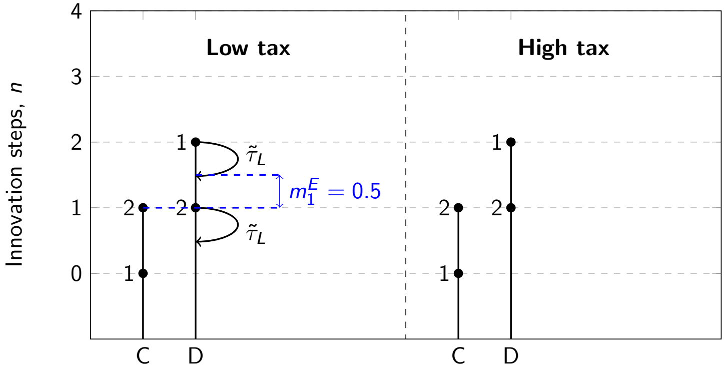

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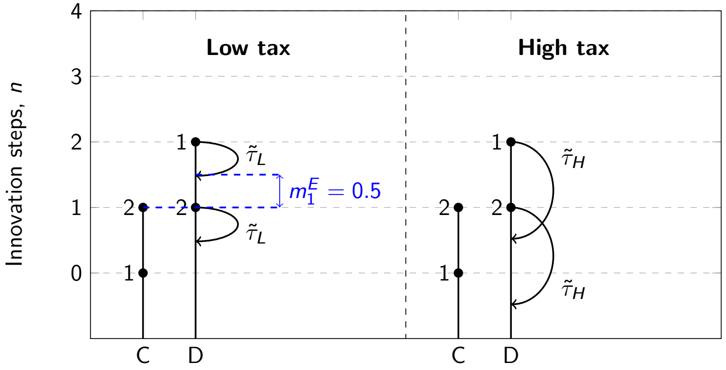

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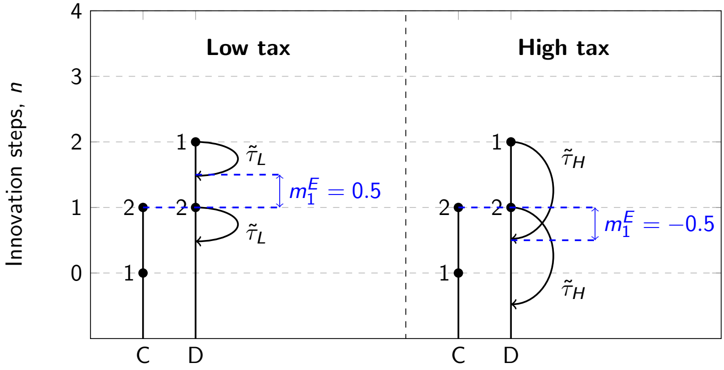

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Stepwise innovation

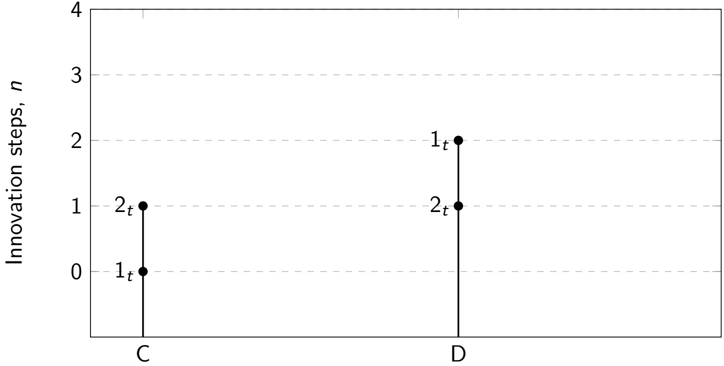

Figure: Clean and dirty innovation

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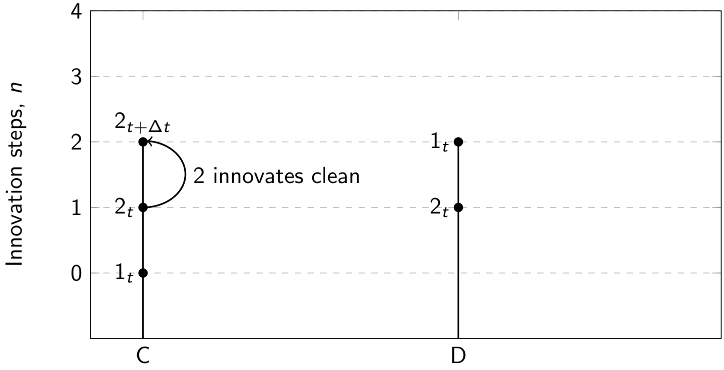

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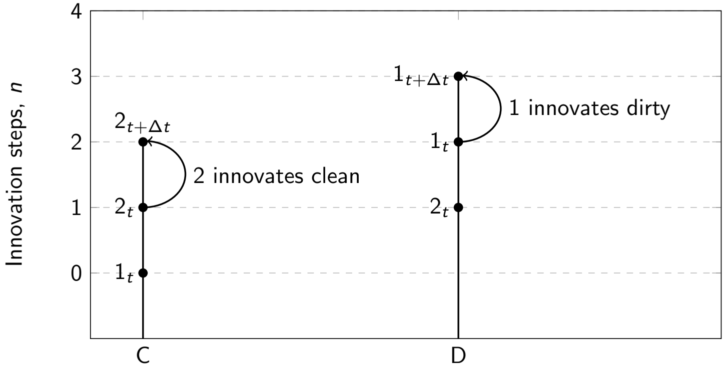

Figure: Clean and dirty innovation

A partial equilibrium result

The increase or introduction of a carbon tax in a single sector can increase a firm's dirty innovation efforts:

- Tax decreases effective technology gap
- Increased competition and innovation due to escape competition effect (Aghion et al., 2005)

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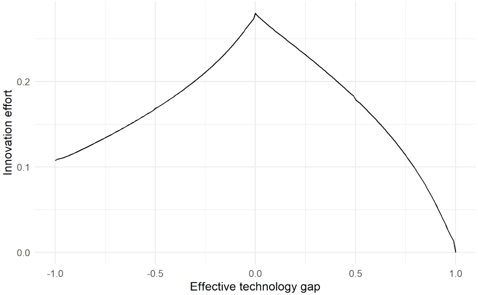

Figure: Innovation efforts for different technology gaps

Calibration

Solve for the general equilibrium in closed form

General equilibrium | BGP | μ_{mt} by group | $w_t, \omega_t, Y_t, E_t, R_t^C, R_t^D$ | Law of motion $Q_t, \psi_{klmt}, \mu_{mt}$

Calibrate model to world economy in 2010s

- External parameters from the literature
- Initial conditions based on patent and financial data
- Internal calibration of remaining parameters following Akcigit and Ates (2023)

External parameters | Initial conditions | Calibration results and model fit

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Two quantitative exercises:

- Simulate BGP: business as usual
- Transition after large carbon tax increase in 2024 (Paris goal in 2100)

Balanced growth path

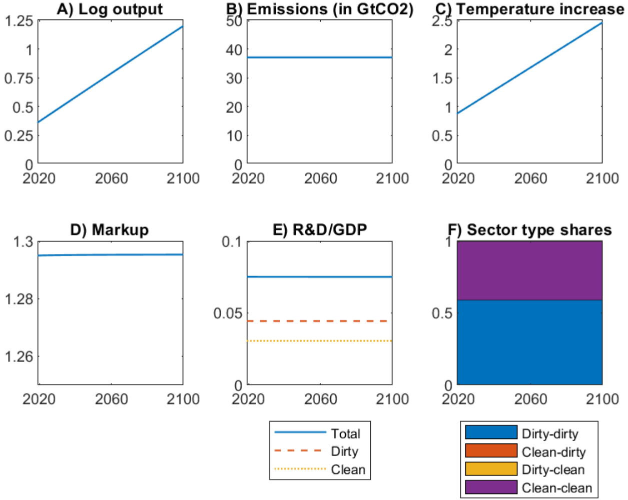

Figure: Balanced growth path simulated forward

The effects of a carbon tax

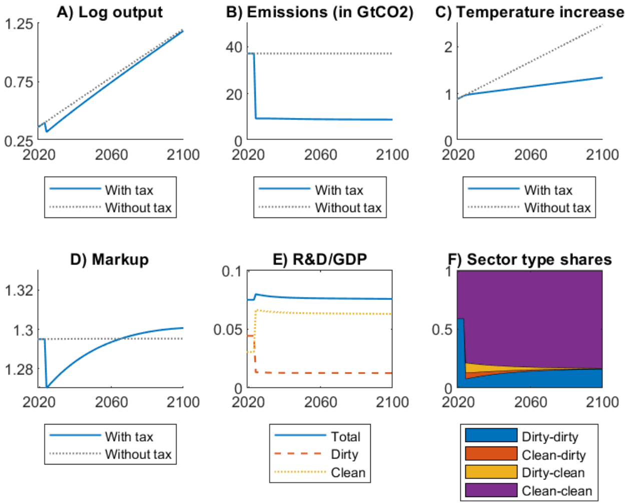

Figure: Transition after a large carbon tax increase in 2024

Conclusions

- Data suggests that market leaders are more invested in dirty technologies than their competitors
- Model shows how this impacts the green transition
  - Some firms increase their dirty innovation
  - Increased innovation and competition along the transition
- Suggests that transition may be less costly than anticipated
  - But it may not be so simple (overinvestment in R&D)
- Considering the strategic incentives for large incumbents is key for a successful green transition

Thanks!

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  - Counts of triadic patent families to avoid double counting and low quality inventions
  - Classified as clean, dirty, neutral following Jee and Srivastav (2023)
  - Mostly energy, manufacturing, transport technologies
  - Link to financial data

Orbis Historical

- Balance sheet and other financial data for millions of firms
  - 2010-2018
  - Mostly developed countries
  - Revenue, employees, profit, age, sector
  - Issues with coverage and representativeness
  - Focus on matched firms and top firms per sector

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Clean and dirty patenting

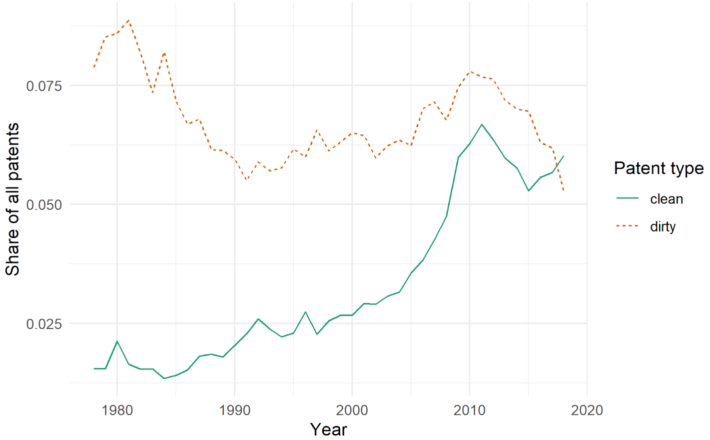

Figure: Share of clean and dirty patents over time

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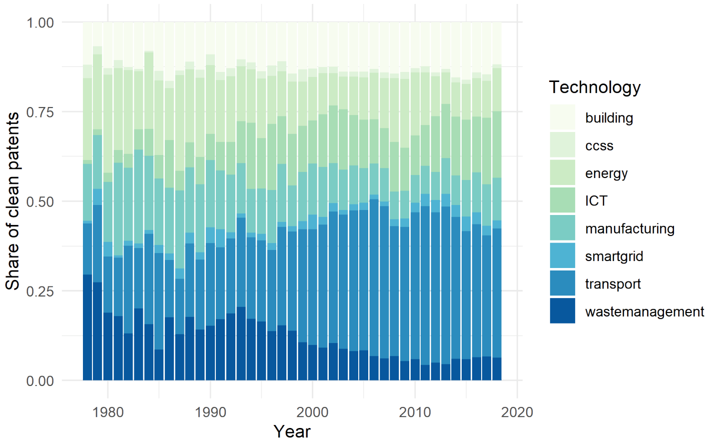
Figure: Different types of clean technologies



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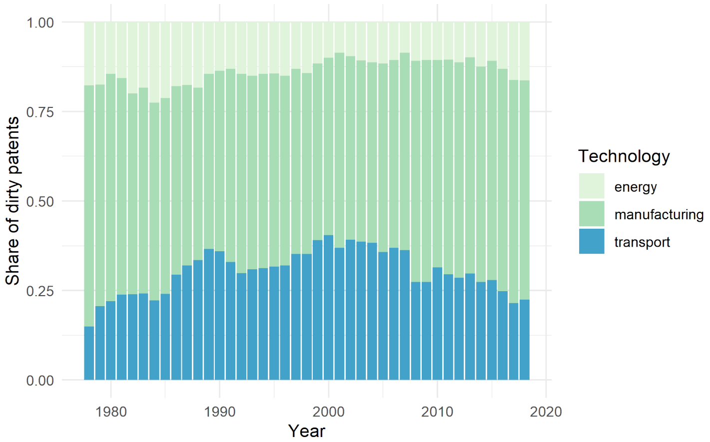

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Figure: Share of gray patents among dirty patents

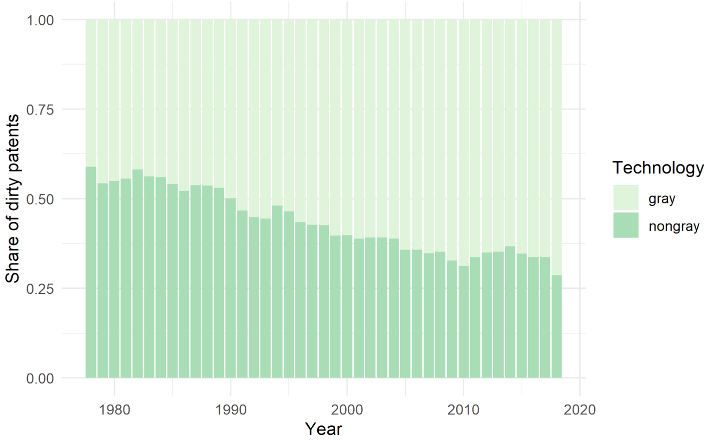

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Figure: Total clean and dirty patents over time

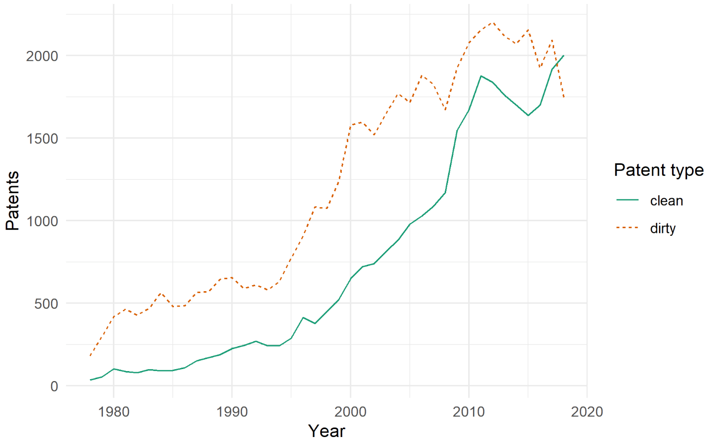

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Figure: Patents by applicant country

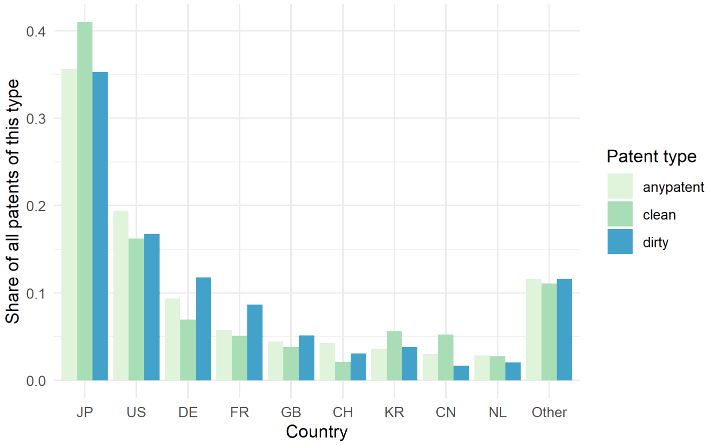

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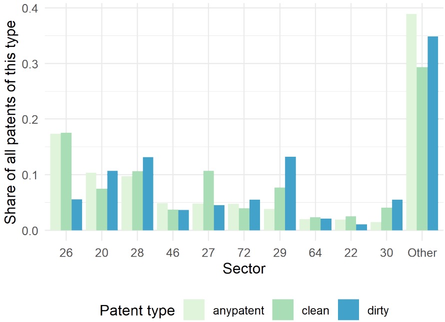
Figure: Patents by applicant sector



Sectors are classified using the NACE Rev. 2 classification. The sectors in the figure are the following. 26: Manufacture of computer, electronic and optical products; 20: Manufacture of chemicals and chemical products; 28: Manufacture of machineryand equipment n.e.c.; 46: Wholesale trade, except of motor vehicles and motorcycles; 27: Manufacture of electrical equipment; 72: Scientific research and development; 29: Manufacture of motor vehicles, trailers and semi-trailers; 64: Financial service activities, except insurance and pension funding; 22: Manufacture of rubber and plastic products; 30: Manufacture of other transport equipment.

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Table: Path dependence in innovation

	(1) Clean	(2) Dirty	(3) Innovation gap (clean-dirty)	(4) Innovation gap (clean-dirty)
Log K^C	0.525***	-0.196***	0.020***	
	(0.021)	(0.013)	(0.003)	
Log K^D	-0.032	0.879***	-0.041***	
	(0.021)	(0.017)	(0.002)	
Technology gap (clean-dirty)				0.241***
				(0.007)
Estimator	Poisson	Poisson	OLS	OLS
(Pseudo) R^2	0.55	0.58	0.12	0.24
Observations	6,624,288	6,624,288	4,215,743	4,112,920

Notes: All independent variables are first lags. OLS regressions include country-sector-year fixed effects (sectors defined at the four-digit level). Further controls in columns 1 through 3 are the stock of patents in any category and dummies that are 1 if the stock variables equal zero (one dummy for each stock). Further controls in column 4 are the stock of patents in any category, a dummy that is 1 if the stock of patents is zero, and a dummy that is 1 if the technology gap is zero. Standard errors are clustered at the firm level. The sample covers the years 1978-2018.

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Table: Technology gaps and market power

	(1)	(2)	(3)	(4)
	Technology gap (clean-dirty)			
Log revenue	-0.005***		-0.004*	
	(0.002)		(0.002)	
Log employment	0.001		-0.001	
	(0.002)		(0.002)	
Profit margin	0.000		0.000	
	(0.000)		(0.000)	
Log age	0.002		0.003	
	(0.002)		(0.003)	
Leader		-0.045***		-0.023***
		(0.011)		(0.006)
Laggard		-0.008		-0.003
		(0.008)		(0.005)
Sectors (for leader and f.e.)	Two-digit	Two-digit	Four-digit	Four-digit
R^2	0.06	0.05	0.16	0.13
Observations	223,088	401,587	208,462	380,164

Notes: All regressions are OLS with country-sector-year fixed effects. Column 2 and 4 define leaders as the top 10 firms in their two-digit and four-digit sector in terms of revenue, respectively. Fixed effects are defined at the two-digit sector in columns 1 and 2 and at the four-digit level in columns 3 and 4. All independent variables are contemporaneous values. Standard errors are clustered at the firm level. The sample covers the years 2010-2018.

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Table: Heterogeneity in technology gaps (four-digit sectors)

	(1)	(2)	(3)	(4)
	Technology gap (clean-dirty)			
Log revenue	-0.003***			
	(0.001)			
Log employment		-0.004***		
		(0.001)		
Profit margin			-0.000	
			(0.000)	
Log age				-0.004***
				(0.001)
R^2	0.13	0.14	0.15	0.10
Observations	372,506	342,421	262,588	835,951

Notes: All regressions are OLS with country-sector-year fixed effects. Fixed effects are defined at the four-digit sector. All independent variables are contemporaneous values. Standard errors are clustered at the firm level. The sample covers the years 2010-2018.

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Preferences, final good, global warming

Representative consumer: $U_t = \int_{s=t}^{\infty} \exp\big(-\rho(s-t)\big)\ln(C_s)ds$,

Labor L is supplied inelastically to production or R&D, $L_t = 1$

Final good: $\ln Y_t = -\frac{\gamma}{2}T_t^2 + \int_0^1 \ln y_{jt}dj$,

with damages from global warming T, scaled by γ

Global warming: $\dot{T}_t = \varepsilon(\zeta S_t - T_t)$,

with ζ the linear effect of cumulative emissions $S_t = \int_0^t E_s ds$ on temperature and ε a delay parameter (Dietz and Venmans, 2019)

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Intermediate good sectors

Firms: each sector j consists of two firms, i and $-i$, which compete on prices

Production: $y_{ijt} = y_{ijt}^C + y_{ijt}^D = q_{ijt}^C l_{ijt}^C + q_{ijt}^D \min\left\{ l_{ijt}^D, \frac{e_{ijt}}{\kappa} \right\}$,

with q productivity, l labor, e emissions, C clean, D dirty

Total costs: $TC_{it} = w_t l_{it}^C + w_t l_{it}^D + \tau_t^E e_{it} = w_t l_{it}^C + w_t(1+\kappa\tau_t) l_{it}^D$,

with w wage and $\tau_t^E = \tau_t w_t$ carbon price relative to labor

Marginal costs: $MC_{it} = \min\{MC_{it}^C, MC_{it}^D\} = \min\left\{ \frac{w_t}{q_{it}^C}, \frac{w_t(1+\kappa\tau_t)}{q_{it}^D} \right\}$

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Innovation

Innovation steps: in case of a successful innovation, $q^F_{i(t+\Delta t)} = \lambda q^F_{it}$,

where $F \in \{C, D\}$

So, $q^F_{it} = \lambda^{n^F_{it}}$, where n^F_{it} is the number of innovation steps that firm i has taken for technology F (assuming $q^F_{i0} = 1$)

Innovation costs: $R_{it} = \alpha \frac{x^{\beta}_{it}}{\beta} w_t$,

where x is the innovation arrival rate

Knowledge diffusion: catch up with leader with exogenous arrival rate δ (technology gap becomes 0)

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Technology gaps

Own, clean, dirty:

Own technology gap: $m_{it}^{T} = n_{it}^{C} - n_{it}^{D}$
Clean technology gap: $m_{it}^{C} = n_{it}^{C} - n_{-it}^{C}$
Dirty technology gap: $m_{it}^{D} = n_{it}^{D} - n_{-it}^{D}$

Firm i uses clean to produce iff $m_{it}^{T} + \tilde{\tau}_t \geq 0$ with $\tilde{\tau}_t \equiv \frac{\ln(1+\kappa\tau_t)}{\ln(\lambda)}$

Effective technology gap:

$$m^E(m_{it}^C, m_{it}^D, m_{it}^T, \tau_t) = \begin{cases} m_{it}^C & \text{if} \quad m_{it}^T + \tilde{\tau}_t \geq 0, \quad m_{-it}^T + \tilde{\tau}_t \geq 0 \\ m_{it}^D + m_{it}^T + \tilde{\tau}_t & \text{if} \quad m_{it}^T + \tilde{\tau}_t \geq 0, \quad m_{-it}^T + \tilde{\tau}_t < 0 \\ m_{it}^C - m_{it}^T - \tilde{\tau}_t & \text{if} \quad m_{it}^T + \tilde{\tau}_t < 0, \quad m_{-it}^T + \tilde{\tau}_t \geq 0 \\ m_{it}^D & \text{if} \quad m_{it}^T + \tilde{\tau}_t < 0, \quad m_{-it}^T + \tilde{\tau}_t < 0 \end{cases}$$

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Static competition

Demand: $y_{jt} = \frac{Y_t}{p_{jt}}$

Bertrand competition: limit pricing:

$$p_{jt} = \begin{cases} MC_{-it} & \text{if} \quad m_{it}^E \geq 0 \\ MC_{it} & \text{if} \quad m_{it}^E \leq 0 \end{cases}$$

Only market leader makes a profit:

$$\pi(m_{it}^E) = \begin{cases} (p_{jt} - MC_{it})y_{it} = \left(1 - \frac{1}{\lambda^{m_{it}^E}}\right) Y_t & \text{if} \quad m_{it}^E > 0 \\ 0 & \text{if} \quad m_{it}^E \leq 0 \end{cases}$$

Also gives each firm's output, labor demand and emissions

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Innovation decision

Direction:

- Currently clean firms ($m_{it}^T + \tilde{\tau}_t \geq 0$) innovate in clean technology
- Currently dirty firms ($m_{it}^T + \tilde{\tau}_t < 0$) innovate in dirty technology

Intensity: maximize NPV of profits given current effective technology gap m

A normalized value function for each possible m: $v_{mt} = V_{mt}/Y_t$

For leaders ($m > 0$):

$$\rho v_{mt} - \dot{v}_{mt} = \max_{x_{mt}} \left\{ 1 - \frac{1}{\lambda^m} - \alpha \frac{x_{mt}^{\beta}}{\beta} \omega_t + x_{mt}[v_{m+1,t} - v_{mt}] \right.$$
$$\left. + x_{-mt}[v_{m-1,t} - v_{mt}] + \delta[v_{0,t} - v_{mt}] \right\}$$

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General equilibrium

Define:

- Maximum effective gap $\overline{m}$
- Maximum distance between clean and dirty $\overline{m}^T$
- Aggregate productivity index $Q_t = \exp\left(\int_0^1 \ln(q_{Ljt}) dj \right)$
- Gap size distribution to keep track of technology gaps (3 state variables per sector): $\psi_{klmt} = \int_0^1 1\left\{ m_{Ljt}^T = k \wedge m_{Fjt}^T = l \wedge m_{Ljt}^E = m \right\} dj$
- Effective gap size distribution $\mu_{mt} = \sum_{k=-\overline{m}^T}^{\overline{m}^T} \sum_{l=-\overline{m}^T}^{\overline{m}^T} \psi_{klmt}$ (by group)

Gives closed form solutions for $\omega_t, E_t, w_t, Y_t, R_t^C, R_t^D$

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Balanced growth

Along the balanced growth path...

- The effective gap distribution is constant
- The gap between clean and dirty within sectors is growing
- There are no "mixed sectors" due to knowledge diffusion
- TFP growth is constant (but, if $E_t > 0$, output growth is not)

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$$\mu_{mt}^{DD} = \sum_{k \in \mathcal{M}_t^D} \sum_{l \in \mathcal{M}_t^D} \psi_{klmt},$$

$$\mu_{mt}^{CD} = \sum_{k \in \mathcal{M}_t^C} \sum_{l \in \mathcal{M}_t^D} \psi_{klmt},$$

$$\mu_{mt}^{DC} = \sum_{k \in \mathcal{M}_t^D} \sum_{l \in \mathcal{M}_t^C} \psi_{klmt},$$

$$\mu_{mt}^{CC} = \sum_{k \in \mathcal{M}_t^C} \sum_{l \in \mathcal{M}_t^C} \psi_{klmt},$$

$$\theta_{1t} = \sum_{m \in \mathcal{M}_t} \mu_{mt}^{DD},$$

$$\theta_{2t} = \theta_1 + \sum_{m \in \mathcal{M}_t} \mu_{mt}^{CD},$$

$$\theta_{3t} = 1 - \sum_{m \in \mathcal{M}_t} \mu_{mt}^{CC}$$

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$$\omega_t = \left(\sum_{k \in \mathcal{M}_t} \frac{\mu_{kt}^{DD} + \mu_{kt}^{CD}}{(1+\kappa\tau_t)\lambda^k} + \frac{\mu_{kt}^{DC} + \mu_{kt}^{CC}}{\lambda^k} \right) \left(1 - \sum_{k \in \mathcal{M}_t} \mu_{kt} (x_{Ljt}^{\beta} + x_{Fjt}^{\beta}) \right)^{-1},$$

$$E_t = \frac{\kappa}{\omega_t} \sum_{k \in \mathcal{M}_t} \frac{\mu_{kt}^{DD}}{(1+\kappa\tau_t)\lambda^k} + \frac{\mu_{kt}^{DC}}{\lambda^k},$$

$$w_t = \frac{Q_t \lambda^{-\sum_{k\in\mathcal{M}_t} \mu_{kt} k} \exp\left(-\frac{\gamma}{2} T_t^2 \right)}{(1+\kappa\tau_t)^{\theta_{2t}}},$$

$$Y_t = \frac{w_t}{\omega_t},$$

$$G_t = \tau_t w_t E_t$$

$$R_t^C = \frac{\alpha w_t}{\beta} \sum_{k \in \mathcal{M}_t} \mu_{kt}^{CD} x_{kt}^{\beta} + \mu_{kt}^{DC} x_{-kt}^{\beta} + \mu_{kt}^{CC} (x_{kt}^{\beta} + x_{-kt}^{\beta}),$$

$$R_t^D = \frac{\alpha w_t}{\beta} \sum_{k \in \mathcal{M}_t} \mu_{kt}^{DD} (x_{kt}^{\beta} + x_{-kt}^{\beta}) + \mu_{kt}^{CD} x_{-kt}^{\beta} + \mu_{kt}^{DC} x_{kt}^{\beta}$$

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$$
\begin{aligned}
\ln(Q_{t+\Delta t}) - \ln(Q_t) =& \Big[2\mu_{0t}x_{0t} + \sum_{k \in \mathcal{M}_{\geq 1t}} \mu_{kt}x_{kt} + \mu_{pt}(x_{pt} + (1-p)x_{-pt}) \\
& + \mu_{1-pt}(x_{1-pt} + px_{p-1t}) \Big] \ln(\lambda)\Delta t + o(\Delta t) \\
\frac{\psi_{k,l,m,t+\Delta t} - \psi_{k,l,m,t}}{\Delta t} =& 1\Big\{ k + 1 + \tilde{\tau}_t < 0 \Big\} \psi_{k+1,l,m-1,t}x_{m-1,t} \\
& + 1\Big\{ k - 1 + \tilde{\tau}_t > 0 \Big\} \psi_{k-1,l,m-1,t}x_{m-1,t} \\
& + 1\Big\{ l + 1 + \tilde{\tau}_t < 0 \Big\} \psi_{k,l+1,m+1,t}x_{-m-1,t} \\
& + 1\Big\{ l - 1 + \tilde{\tau}_t > 0 \Big\} \psi_{k,l-1,m+1,t}x_{-m-1,t} \\
& - \psi_{k,l,m,t}(x_{m,t} + x_{-m,t} + \delta) + \frac{o(\Delta t)}{\Delta t} \\
\frac{\mu^{FF}_{m,t+\Delta t} - \mu^{FF}_{m,t}}{\Delta t} =& \mu^{FF}_{m-1,t}x_{m-1,t} + \mu^{FF}_{m+1,t}x_{-m-1,t} \\
& - \mu^{FF}_{m,t}(x_{m,t} + x_{-m,t} + \delta) + \frac{o(\Delta t)}{\Delta t}
\end{aligned}
$$

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Calibration

Assume world economy is on a BGP in 2010s

Parameter	Value	Description	Source
ρ	1%	Rate of time preference	Acemoglu et al. (2016)
β	1/0.35	R&D cost curvature	Akcigit and Ates (2023)
γ	0.01	Climate damage elasticity	Dietz and Venmans (2019); Nordhaus and Moffat (2017)
ζ	0.00048×1.1	TCRE	Dietz and Venmans (2019); Matthews et al. (2009)
ε	0.5	Initial pulse-adjustment time-scale of the climate system	Dietz and Venmans (2019); Ricke and Caldeira (2014)

Table: Externally calibrated parameters

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Calibration

Initial conditions:

- Initial share of clean and dirty firms
- Emissions since 1850 to compute initial (2019) temperature
- Initial gap distribution
  - Define leaders as firm with highest absolute value of m^T (as defined in empirical section)
  - Classify sectors as clean or dirty based on leader
  - Laggard is second firm in terms of m^T
  - Fill in $\Psi_{m=0,t=0}$ using BGP effective gap distribution

Calibration

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Internal calibration procedure similar to Akcigit and Ates (2023):

- For given $\{\lambda, \delta, \alpha, \kappa\}$, find BGP effective gap size distribution
- Compute model moments
- Minimize difference with data moments

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Calibration

Parameter	Value	Description
λ	1.0656	Innovation step size
δ	0.0374	Diffusion arrival rate
α	44.4299	R&D scaling parameter
κ	68.5578	Emission scaling parameter

Table: Internally calibrated parameters

Moment	Model	Data	Source
Average markup (2015)	1.2953	1.29	Díez et al. (2021)
Profit share (2018)	19%	19%	Eggertsson et al. (2021)
Productivity growth (avg. 2011-2019)	1.0738%	1.0738%	OECD
Emissions (2019, in $GtCO_2$)	37.0826	37.0826	Friedlingstein et al. (2022)

Table: Model fit

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