Is technology adoption skill-biased?

The case of green technological change

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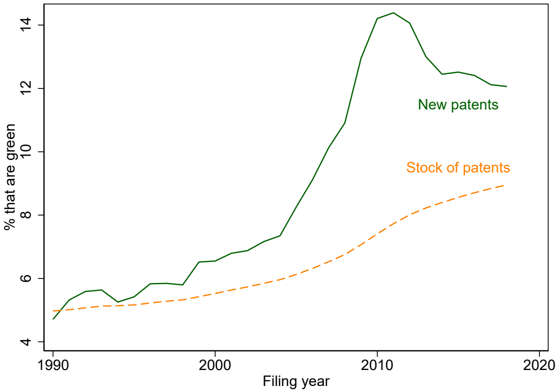
Green technology increasingly important



Note: Share of triadic patent families (registered in the EU, US and Japan). Classified as green using the Y02 framework.

Green, solid line: Share of new patents filed each year. Orange, dashed line: Share of stock.

Green technology and skill

What I do

Research question: Is green technology skill-biased?

Exploit Norwegian administrative data to identify the effect of the firm adopting green technology on

(a) relative wages of high-skilled workers in the firm (*wage premium*)

(b) share of high-skilled employees among the firm's workers (*skill share*)

Instrument for technology adoption with global technological advancement
$\rightarrow$ Treat global innovations (patents) as shocks to which firms are differentially exposed through their import mix

Preview of results

Green technology is skill-biased, with a stronger relationship in some sectors than others

The skill-bias of green technology is similar to that of other technologies
→ Weak evidence that green is slightly more skill-biased
→ Whether the green transition contributes to increased wage inequality depends in part on whether green technology comes in addition to, or instead of, other types of technology

There is a clear pre-trend on the skill-bias of technology
→ Calls for an identification strategy that contains exogenous variation.

Contributions to the existing literature

Skill-biased technological change: New instrument & firm-level data, green specific

Lindner et al. (2022), Bøler (2015), Caroli and Van Reenen (2001), Autor, Katz and Krueger (1998) and Juhn, Murphy and Pierce (1993)

Directed technological change: Application of skill-bias to green technology

Acemoglu (2002), Acemoglu et al. (2012) and Aghion et al. (2016)

Labour market effects of climate policy or green technology: Empirical evidence

Dix-Carneiro, Hedne, Isaksen and Traiberman (in progress), Azevedo, Wolff and Yamazaki (2023), Saussay et al. (2022), Sato et al. (2019), Vona et al. (2018) and Yip (2018)

Innovation, technology adoption and trade: Global technology spillovers and (green) adoption

Coelli, Moxnes and Ulltveit-Moe (2022), Coe and Helpman (1995) and Berkes, Manysheva and Mestieri (2022)

Roadmap

Conceptual framework

Each firm produces an homogenous final good using clean and dirty intermediate production

- Clean technology adoption increases the TFP of clean production and vice versa
- Both clean and dirty production use both high- and low-skilled labour
- High-skilled labour allowed to have different returns in clean than dirty production
- Firms face heterogeneous labour supply curves (workers have heterogeneous preferences over each firm) and optimise production by setting high- and low-skilled wages

Model setup

Firms:

- Clean and dirty intermediate production combined to one output

$$Y_j = \left[Y_{Cj}^{\frac{\rho-1}{\rho}} + Y_{Dj}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \qquad \rho > 1 \tag{1}$$

Model setup

Firms:

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- Both clean and dirty production use high- and low-skilled labour

Model setup

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- Clean and dirty intermediate production combined to one output

$$Y_j = \left[Y_{Cj}^{\frac{\rho-1}{\rho}} + Y_{Dj}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \qquad \rho > 1 \tag{1}$$

- Both clean and dirty production use high- and low-skilled labour
- Clean and dirty production can differ in their technology A and different returns to skill γ

$$Y_{sj} = A_{sj} \left[\gamma_s L_{Hsj}^{\frac{\sigma-1}{\sigma}} + L_{Lsj}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \qquad s = C, D \tag{2}$$

Model setup

Workers have idiosyncratic preferences over working at different firms (Card et al. 2018), leading to heterogeneous labour supply

$$u_{iqj} = \beta \ln(w_{qj}) + a_{qj} + \varepsilon_{iqj} \qquad q = H, L \tag{3}$$

$$\ln L_{qj}(w_{qj}) = \ln(L_q \lambda_q) + \beta_q \ln(w_{qj} - b_q) + a_{qj} \tag{4}$$

Green technology is skill biased if an increase in green relative to dirty technology increases the relative marginal product of high-skilled labour:

$$\frac{\partial MPL_H / MPL_L}{\partial A_C / A_D} > 0 \tag{5}$$

Model predictions

1. Green technology changes the relative marginal product of labour if it leads to a *reallocation of production* to production that is more or less skill-intensive
2. The impact on relative MPL depends on whether green or dirty technology is more skill-intensive, and whether high- and low-skilled labour are substitutes or compliments
3. When high- and low-skilled labour are substitutes ($\sigma > 1$), green technology is skill-biased if and only if high-skilled labour is relatively more productive in the green sector ($\gamma_C > \gamma_D$).

Data

Administrative data provided by Statistics Norway

- Firms: Economic activity
  - *Innovation survey (CIS):* Whether or not they adopt new technology (dummy)
    - Green technology: Whether reduced environmental impact was a purpose (2008–2016)
  - Customs declarations: Import of 6-digit goods, country of origin, etc.
- Workers: Link to firms, job & income details, demographic variables

Patent data from PATSTAT

▸ Summary statistics

What is green technology?

Binary variables from survey:

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   $\rightarrow$ Technology adoption $= 1$ if yes, 0 if no

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   $\rightarrow$ Green technology adoption = 1 if "some" or "great" importance, 0 if "low" or "not applicable"

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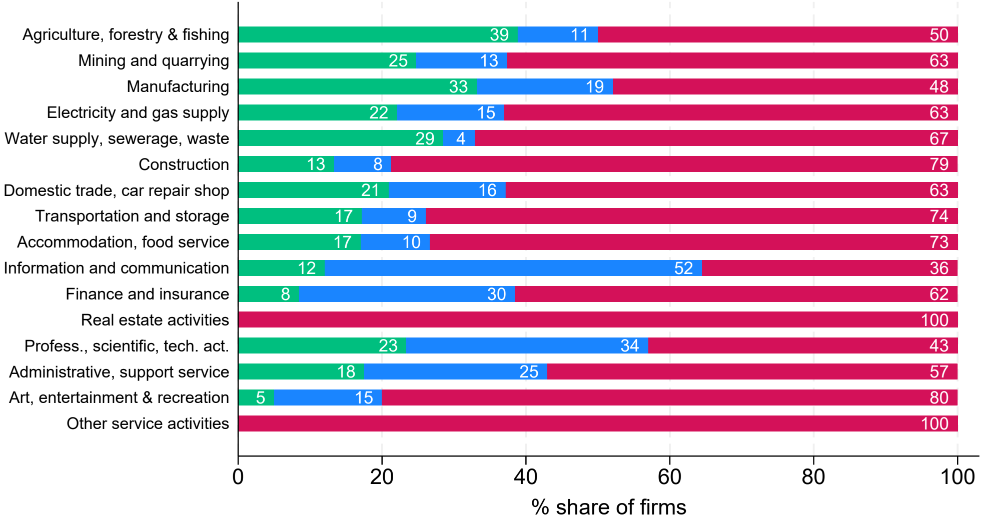
Most technology adoption is not new to the firm's market (40 %)

Each "wave" covers a three-year period

All firms with more than 50 employees, a stratified sample of smaller firms

Share of technology adoption per sector



Baseline: Identification

Inspired by Lindner et al. (2022): Same coefficient on both wage premium and skill share to rules out increased high-skilled labour supply or firm demand shocks

Exploit richness of data to absorb many potential confounders

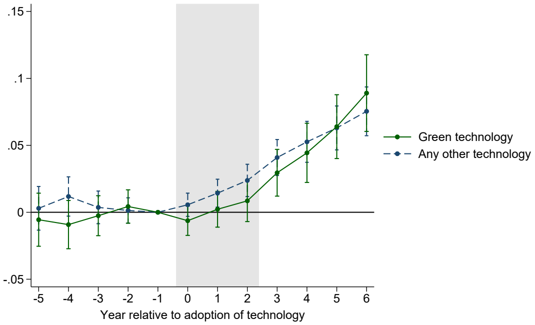
$$\ln \text{skill share}_{jt} = \sum_{\tau=-5}^{5} \text{GI}_{j,t-\tau} \beta_{\tau}^{ss} + X_{jt}\lambda^{I} + + \delta_{nt} + \nu_{jt}$$

$$\begin{aligned} \ln \text{wage}_{ijt} = & \sum_{\tau=-5}^{5} \text{GI}_{j,t-\tau} \times \mathbb{1}[\text{higher education}_{ij,t-\tau}] \beta_{\tau}^{wp} \\ & + \sum_{\tau=-5}^{5} \text{GI}_{j,t-\tau} \beta_{\tau}^{GI} + X_{ijt}\lambda^{GI} + \delta_{nt} + \nu_{ijt} \end{aligned}$$

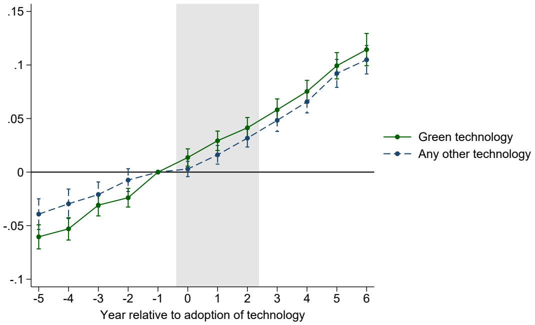
for worker i in firm j, industry n and time t. $\text{GI}_{jt} = \text{technology adoption}_{jt} = 1$ if firm j has adopted new technology during the current wave, 0 otherwise. Standard errors cluster on firm level.

Baseline results (OLS)

Skill share $\ln(L_H/L)$



Wage premium $\ln(w_H/w_L)$



▸ Pooled LD (green tech)

Shift-share instrumental variable strategy

While previous strategy identifies the complementarity between skill and technology, there could still be reverse causality

Source of exogenous variation in incentives to adopt (green) technology: Exogenous global technology shocks (patents) to which firms are differentially exposed depending on what and from where they import

Firms that trade more in goods with novel technology are more likely to adopt new technology

- Direct technology adoption through import of more advanced capital goods
- Changed production possibilities from more advanced intermediate inputs
- Indirect learning from technology embodied in the good

Exposure to (green) technological advancement

Exposure to (green) technological advancement

Technology class 1

Technology class 2

Technology class 3

Technology class 4

Exposure to (green) technological advancement

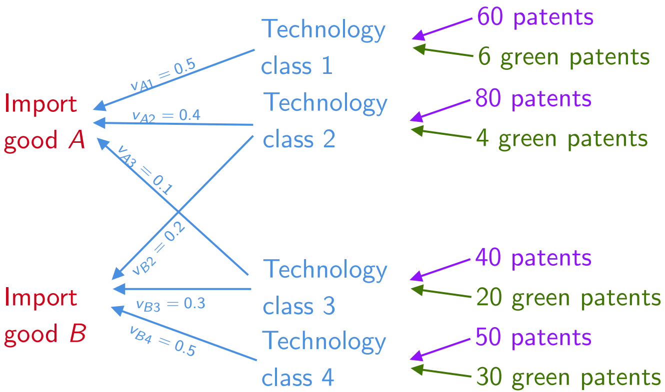
Technology class 1 ← 60 patents
Technology class 1 ← 6 green patents

Technology class 2 ← 80 patents
Technology class 2 ← 4 green patents

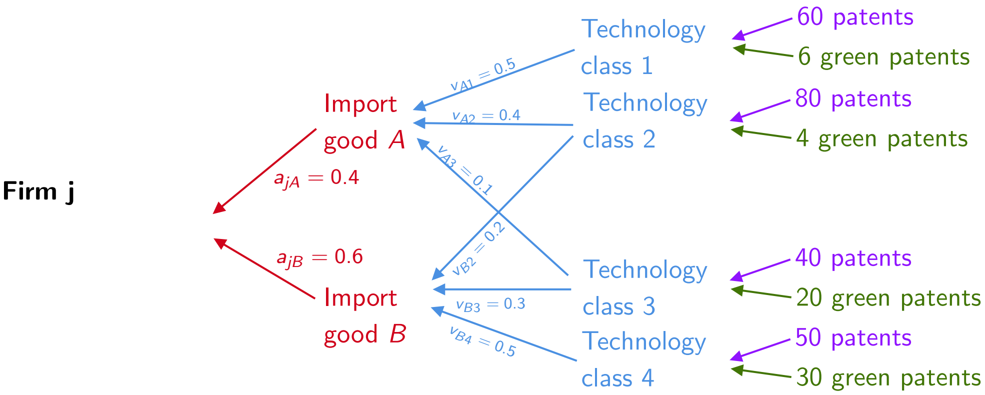
Technology class 3 ← 40 patents
Technology class 3 ← 20 green patents

Technology class 4 ← 50 patents
Technology class 4 ← 30 green patents

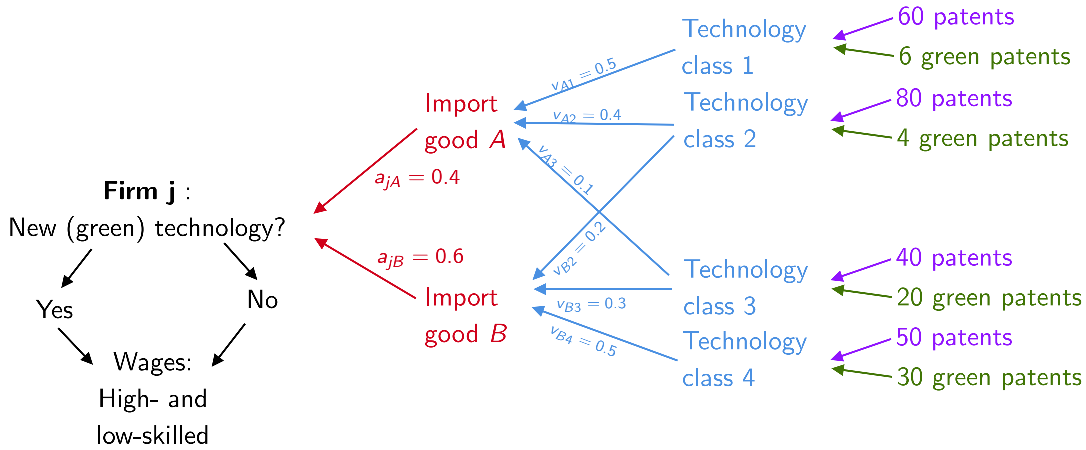
Exposure to (green) technological advancement



Exposure to (green) technological advancement



Exposure to (green) technological advancement



Definitions

- Triadic patents: Patent families that have patents registered in US, Japan, EU
- Green patents: European Patent Office's Y02 classification (excluding adaptation)
- Imported goods: Value of each firm j's import of each good g and country h in year t. Goods are linked to technology classes classes using a probabilistic crosswalk provided by Goldschlag, Lybbert and Zolas (2016)
    - Goods follow the harmonized standard (HS), 4-digit
    - Technology classes are four-digit CPC

Green patents: CPC Climate mitigation technologies (EPO)

CPC code	Name
Y02A	Adaptation to climate change
Y02B	Buildings
Y02C	Capture and storage of greenhouse gases
Y02D	ICT aiming at the reduction of own energy use
Y02E	Production, distribution and transport of energy
Y02P	Industry and agriculture
Y02T	Transportation
Y02W	Waste and wastewater

Formal definition of instrument(s)

Captures the *variation in global technological advancement* that the firm is exposed to through its historical import mix. Instrument for *any* technology adoption using all patents, and *green* technology adoption using green patents.

SSIV: $z_{jt} = \sum_n s_{jk} g_k$ (Borusyak, Hull and Jaravel 2022). Here:

$$z_{jt} = \sum_{g,h} \text{import share}_{jgh,0} \sum_k v_{ghk} * \text{number of (green) patents}_{hkt}$$

- j denotes firm, t year, g import good, h (foreign) country and k CPC technology class
- Import share: Average share of import value from each good g, country h pair for firm j between 2002 and 2007 ($\frac{\sum_{t=2002}^{2007} \text{import value}_{jght}}{\sum_{g,h} \sum_{t=2002}^{2007} \text{import value}_{jght}}$)
- v_{gk} are probabilistic importance weights from Goldschlag, Lybbert and Zolas (2016)

Identification

Identification follows Borusyak, Hull and Jaravel (2022) and Borusyak and Hull (2023)

- Exclusion restriction: Global patenting is not correlated with unobserved firm-level shocks in Norway (Many and uncorrelated shocks)
- Endogenous shares: Recenter variable using *expected shock*, i.e.

$$\ln \overline{\text{patent stock}}_{hkt} = \ln \text{patent stock}_{hkt} - \ln \left(\frac{1}{6} \sum_{s=2000}^{2005} \text{patent stock}_{hks} \right)$$

- Relevance: Global patenting affects firm technology adoption + assumption on shares
- Monotonicity: The effect is positive for all firms

IV specification

First stage:

$$\text{GI}_{jt} = z_{j,t-2}\gamma + \delta_{nt} + \zeta_{jt}$$

where z_{jt} comes in three forms:

- $z_{j,t-2} = \ln \overline{\text{green patent stock}}_{hk,t-2}$
- $z_{j,t-2} = \ln \left(\overline{\text{green patent stock}}_{hk,t-2} / \overline{\text{patent stock}}_{hk,t-2}\right)$
- $z_{j,t-2} = \ln \overline{\text{patent stock}}_{hk,t-2}$ instruments for any technology adoption

Second stage:

$$\ln \text{skill share}_{jt} = \hat{\text{GI}}_{jt}\beta^{ss-IV} + \delta_{nt} + \nu_{jt}$$

$$\ln \text{wage}_{ijt} = \hat{\text{GI}}_{jt} \times \mathbb{1}[\text{higher education}_{ijt}]\beta^{wp-IV} + \hat{\text{GI}}_{jt}\beta^{GI-IV} + \delta_{nt} + \nu_{ijt}$$

▸ shock summary statistics ▸ weight summary statistics

First stage results (preliminary)

	(1)	(2)	(3)	(4)
L2.log(green patent stock)	0.00982*	0.0491**	0.00512	0.0557*
	(0.00407)	(0.0165)	(0.00591)	(0.0243)
Firm heterogen		recentered		recentered
Control group	1	1	2	2
F-statistic	5.815	8.882	0.749	5.253
Observations	6222	6222	3105	3105
L2.log(green share of patent stock)	0.144	0.0906***	0.225	0.0870*
	(0.0853)	(0.0270)	(0.167)	(0.0427)
Firm heterogen		recentered		recentered
Control group	1	1	2	2
F-statistic	2.853	11.21	1.804	4.157
Observations	6222	6222	3105	3105

Industry-by-time FE. Standard errors clustered on firm. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

▸ Any technology

Conclusion

Green technology is associated with increased skill demand

The relationship between green technology and skill demand is similar to that of other types of technology
$\rightarrow$ Whether a green transition increases the demand for skill is likely to depend on whether green technology comes *in addition to* or *crowds out* other technologies

Being exposed to more green technology shocks increases the probability of a firm adopting green technology

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Summary statistics: Firms

	Population	Subsample: Innovation survey
Employees	5.664	46.01
	(95.52)	(244.4)
Share in manufacturing	0.0429	0.282
	(0.203)	(0.450)
Physical capital	27 945.9	146 966.7
	(1 307 911.3)	(3 597 700.8)
Technology adoption		0.406
		(0.491)
Green technology adoption		0.266
		(0.442)
Observations	18 250 640	449 077
Number of firms	2 191 786	25 475

Detailed version

Summary statistics: Firms (full population vs subsamples)

	Population	Innovation survey	Importers	Sample
Employees	5.664	46.01	64.93	80.14
	(95.52)	(244.4)	(320.9)	(379.6)
Share in manufacturing	0.0429	0.282	0.350	0.366
	(0.203)	(0.450)	(0.477)	(0.482)
Technology adoption		0.406	0.468	0.487
		(0.491)	(0.499)	(0.500)
Green technology adoption		0.266	0.300	0.308
		(0.442)	(0.458)	(0.462)
Exposure to patents			3134.2	2753.5
			(5546.3)	(4955.0)
Exposure to green patents			244.5	244.2
			(452.2)	(434.2)
Observations	18250640	449077	189139	85070
Number of firms	2191786	25475	21744	9686

Results

Relationship between wage premium and firm-level adoption of green innovation

	(1)	(2)	(3)	(4)
Green technology	-0.0116	-0.00818	-0.00459	-0.00372
	(0.00752)	(0.00736)	(0.00819)	(0.00800)
Green x Education	0.0242**	0.0243**	0.0144	0.0168*
	(0.00787)	(0.00821)	(0.00829)	(0.00825)
Control group	1	1	2	2
Mincer controls		✓		✓
Education FE	✓	✓	✓	✓
Industy x year FE	✓	✓	✓	✓
Firm-year observations	11665	11665	6467	6467
Worker-year observations	403834	403780	326534	326479

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

▸ Skill share ▸ Any tech ◂

Results

Relationship between skill share and firm-level adoption of green innovation

	No tech adoption		Other tech adoption	
	(1)	(2)	(3)	(4)
Green technology	0.0432***	0.0641***	0.0137	0.0104
	(0.0126)	(0.0141)	(0.0143)	(0.0157)
Firm controls		✓		✓
Industy x year FE	✓	✓	✓	✓
Observations	9051	7493	5611	4746

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results

Wage premium ($\ln \frac{w_H}{w_L}$)

	(1)	(2)
Technology adoption	-0.00866	-0.00557
	(0.00611)	(0.00603)
Technology x Education	0.0262***	0.0248**
	(0.00757)	(0.00783)
Mincer controls		✓
Education FE	✓	✓
Industy x year FE	✓	✓
Firm-year observations	13908	13908
Worker-year observations	460265	460209

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Skill share ($\ln \frac{L_H}{L}$)

	(1)	(2)
Technology adoption	0.0440***	0.0643***
	(0.0109)	(0.0124)
Firm controls		✓
Industy x year FE	✓	✓
Observations	11070	9173

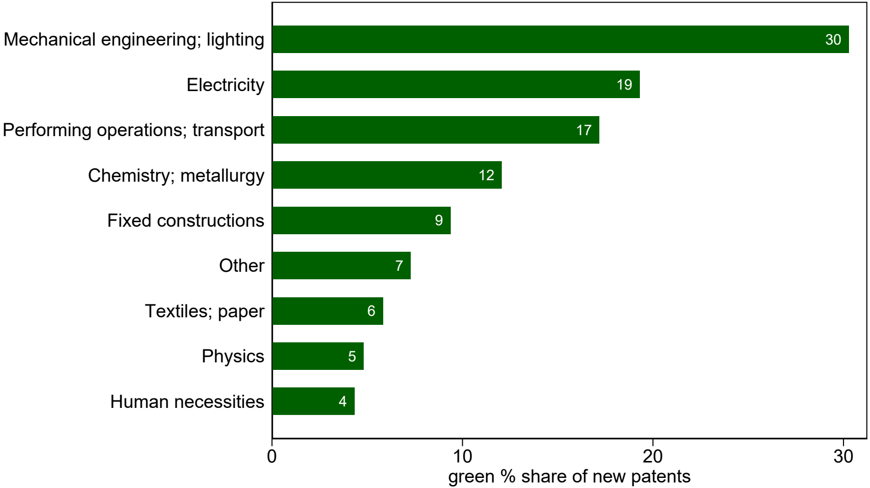
Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors (clustered on firm) in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Share of green in CPC technology classes



Shock summary statistics

	Mean	SD	IQR
Patent stock			
Base	4.85	2.13	2.84
Residualised on year FE	0.00	2.13	2.85
Recentered on 2000–2005 mean	0.34	0.29	0.29
Year FE & recentered	0.00	0.28	0.28
Green patent stock			
Base	2.35	1.94	2.94
Residualised on year FE	0.00	1.94	2.91
Recentered on 2000–2005 mean	0.54	0.53	0.72
Year FE & recentered	0.00	0.51	0.65
Green share of patent stock			
Base	0.06	0.12	0.06
Residualised on year FE	0.00	0.12	0.06
Recentered on 2000–2005 mean	0.17	0.41	0.44
Year FE & recentered	0.00	0.40	0.43
Observations	150639	150639	150639

Weight summary statistics

Summary statistics as in Borusyak, Hull and Jaravel (2022, table 1)

Largest weight	0.00709
Effective sample size (1/HHI)	234.6
No. of technology classes	639
No. of countries	88
No. of tech class x countries	24846

First stage results: Any technology

	(1)	(2)	(3)
L2.log(patent stock)	0.0143***	-0.00676	0.0866**
	(0.00415)	(0.00889)	(0.0283)
Firm heterogen		Firm FE	recentered
Control group			
F-statistic	11.88	0.579	9.346
Observations	8668	6477	8668