

The social and environmental consequences of the twin energy-digital transition

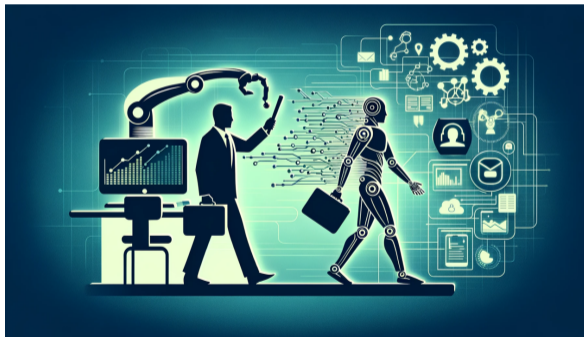
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How do technological transitions affect jobs and the environment?

- ▶ The ongoing process of **automation** (e.g. computer numerical control machinery, industrial robots, and AI) is associated with:
 - ▶ **displacement of labor** and **low wage growth** (Acemoglu et al., 2022)
 - ▶ job **polarization** (Goos et al., 2014)
- ▶ Effect of innovation on **environment** and **emissions** less well understood



Two paradigm shifts shape the future of work: **digital & green**



- ▶ Large **green investments** to facilitate the transition towards carbon neutrality expected to **boost job creations** and **change skills demand**
- ▶ Potential **technical synergies** expected between the “**twin**” **green** and **digital** transitions







Our contributions

- ▶ **Novel measure of establishment-level innovation exposure**
 - ▶ Using detailed **online job vacancy** data to construct an **establishment-level** measure of the **skill content** of work
 - ▶ First **patent-level** link between technological **innovations** and occupational **skills**
- ▶ Is **green** innovation **labor-augmenting** or **labor-saving**?
- ▶ **Causal impact of green and automation innovation on employment**
 - ▶ Implement a **shift-share design** at the establishment level
 - ▶ Assess occupational and industry employment and wage impacts
- ▶ **And on greenhouse gas emissions**
 - ▶ Using **establishment-level emissions** data
 - ▶ Estimate the **causal effect** of **technology** exposure on **emissions**

Contributions to the literature

1. **Employment impacts of the green transition** (Consoli et al., 2016; Vona et al., 2019; Marin and Vona, 2019; Popp et al., 2022; Saussay et al., 2022; Curtis and Marinescu, 2023; Curtis et al., 2023) [▶ Details](#)
2. **Technical change, jobs and skills** (Acemoglu and Autor, 2011; Harrigan et al., 2021; Acemoglu et al., 2022; Autor et al., 2024; Kogan et al., 2023; Hémous et al., 2024; Babina et al., 2024) [▶ Details](#)
3. **Measurement of firms' exposure to innovation / technology adoption** (Montobbio et al., 2021; Kogan et al., 2023; Mann and Püttmann, 2023; Rughi et al., 2023; Prytkova et al., 2024; Babina et al., 2024; Hémous et al., 2024) [▶ Details](#)
4. **Twin green-digital transitions** (Andres et al., 2022; Bianchini et al., 2023) [▶ Details](#)

Conceptual framework: green and automation innovation's impacts

	Effect on labor	Effect on high-skilled demand	Effect on emissions
Green innovation			
	Depends if saving or augmenting	But only on STEM	
Automation innovation			
			Productivity vs size effect

How to measure firms' adoption of green technology?

- ▶ **General challenge:** How to measure the extent to which firms **benefit** from **technological innovation**?
- ▶ Requires a measure of **establishment-level** technological **adoption**
 - ▶ Traditional measures like **patent counts** only capture **innovation**, not **adoption**
- ▶ **Our approach:** we introduce a **new measure** of firms' **adoption** of **green technology** using **job postings** data
 - ▶ **Skills** that firms seek in **job ads** provide **firm-specific** data on **work performed**
 - ▶ In turn, these skills also contain information on the **technologies** used in the firm's **production process**
 - ▶ Used to measure e.g. AI and labor saving adoption (Acemoglu et al., 2022; Autor et al., 2024)
- ▶ We build a **link** between **patents** and **skills**

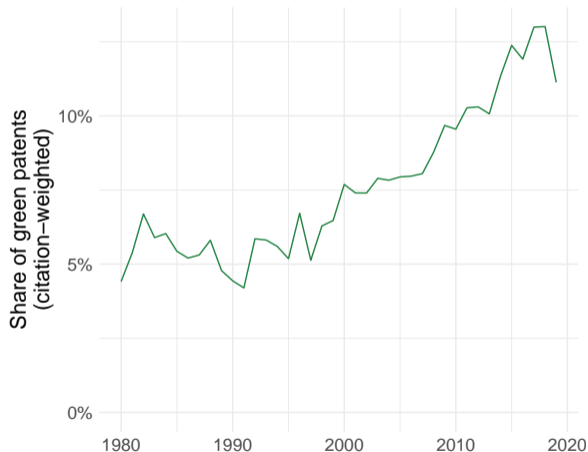
Data – Lightcast online job postings data

- ▶ Collects raw text from online job ads through extensive web scraping of **50,000+ online sources** (job boards and company websites)
- ▶ Structured data: Cleans and codifies raw text and provides it in a usable format
- ▶ Covers the universe of US online job postings, around **330 million job ads** for 2010-2024
- ▶ Standardised variables including:
 - ▶ **Occupational** category (SOC code)
 - ▶ **Skills required**
 - ▶ **Wage** offered
 - ▶ **Education** requirements
 - ▶ **Company name**
 - ▶ **Location of job**
- ▶ Skills codified into a hierarchical taxonomy of **32,000+ unique skills**, grouped into skill categories and sub-categories

Data – Google Patents Public Data

- ▶ **Worldwide bibliographic** coverage since 19th century
- ▶ For each **patent**, we observe:
 - ▶ **Cooperative Patent Classification** (CPC) codes
 - ▶ **Title**
 - ▶ **Abstract**
- ▶ We only include patents meeting a certain **quality threshold**:
 - ▶ **Triadic patents** – filed at 3 major patent offices: EPO, JPO and USPTO
 - ▶ Received **at least one citation**
- ▶ **1.6 million** triadic **patents** from **1980-2019** in our sample

Data – Identifying green innovation



► We rely on the **CPC classification**:

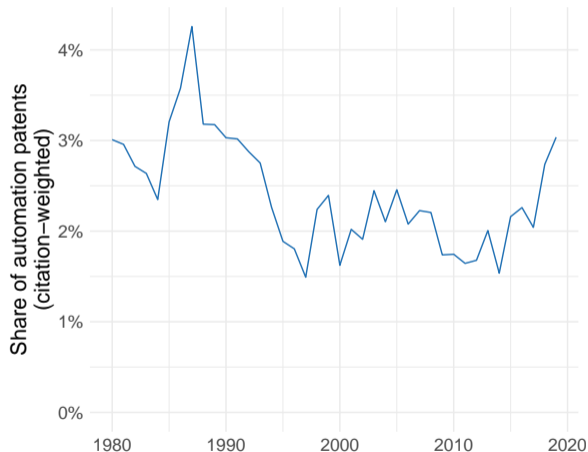
- **Y02**: Technologies or Applications for Mitigation or Adaptation Against **Climate Change**
- **Y04S**: Systems Integrating Technologies Related to Power Network Operation [...] i.e. **Smart Grids**

► [Details](#)

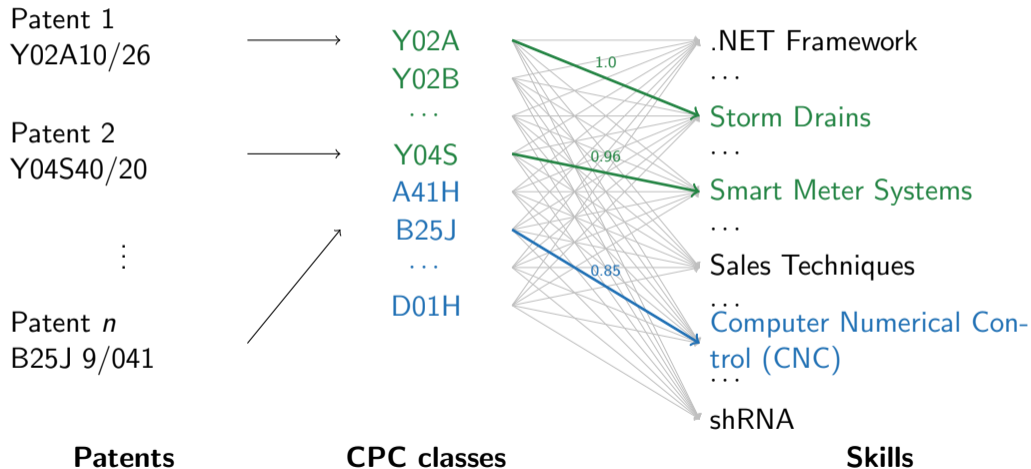
Data – Identifying automation innovation

- ▶ We use 6-digits CPC codes identified by **Hemous et al. (JPE forth.)**:
 - ▶ Focus on **machinery** innovation
 - ▶ **Keyword**-based approach
 - ▶ Dominated by **industrial robots** in the 1980s and **digital automation** in the 2010s

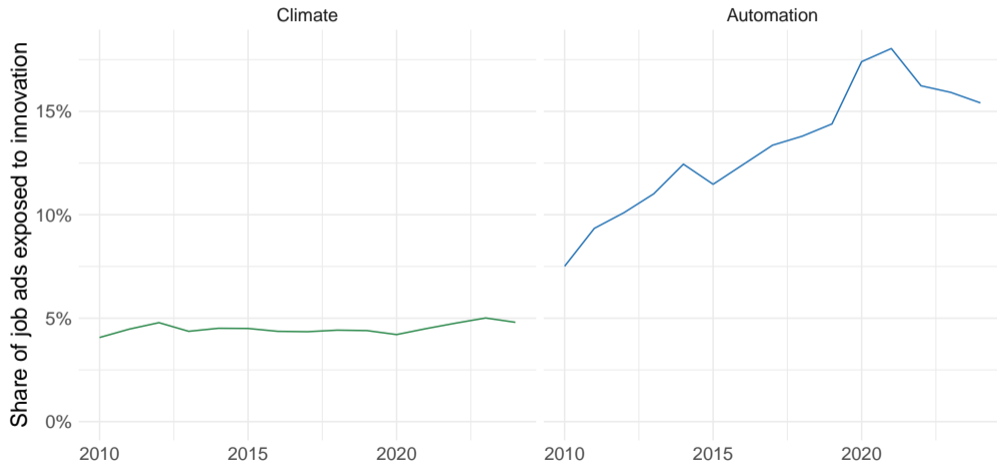
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Linking patents to skills using semantic similarity



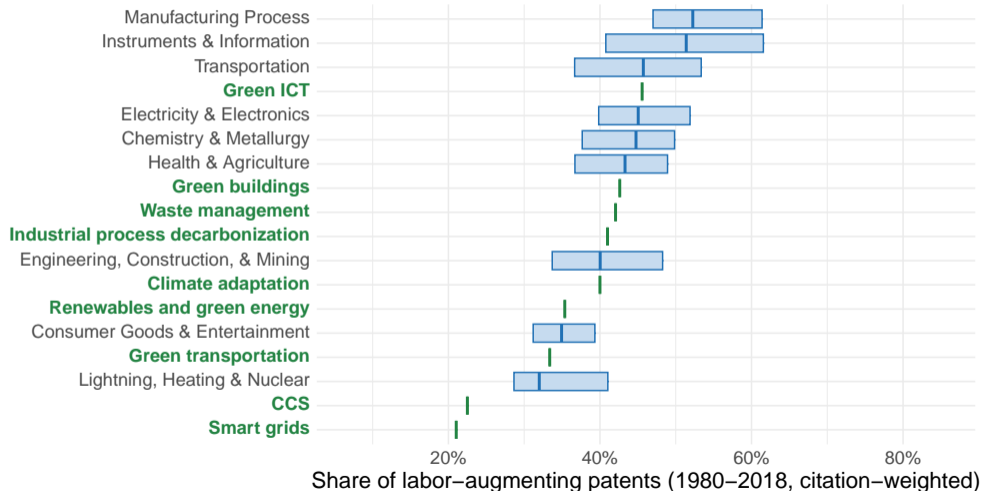
Share of ads exposed to green and automation technology



How to identify labor-saving and labor-augmenting innovation?

- ▶ Adopt **Autor et al. (2024 QJE)** empirical approach
- ▶ **Labor-saving** innovations **replace tasks** currently performed by workers
 - ▶ Therefore the **textual** content of **labor-saving patents** should be **semantically similar** to descriptions of **occupational tasks**
- ▶ **Labor-augmenting** innovations **complement** workers' occupational outputs
 - ▶ **Textual** content of **labor-augmenting patents** should be **semantically similar** to descriptions of **new occupational titles**
- ▶ We implement this method on our corpus of **1.6 million patents** to estimate the **ratio** of **labor-augmenting** to **labor-saving** innovation in each **green technology class**

Green innovation's labor impact is expected to be heterogeneous



Technology adoption impacts on labor & emissions

- ▶ Using our **job ads dataset**, we can construct our **novel measure** of **green** and **automation** innovation **adoption** over **15 years** at the regional, firm or even **establishment level**
- ▶ **What is the causal impact of an increase in innovation adoption on labor and environmental outcomes?**
- ▶ We consider **long differences** over a decade-long period
 - ▶ Recognizing that technological diffusion is not an instant process
- ▶ To address the risk of reverse causality, we **instrument** the change in green and automation adoption using innovations in these technology classes **outside the firm**

Instrumenting change in tech adoption: Shift-share IV design

Our measure of **technological adoption** at the **establishment**-level can be written as:

$$S_{iK,t} = \sum_{k \in K} S_{ik,t}^{ads} \quad \text{where} \quad S_{ik,t}^{ads} = \frac{\sum_{a \in \mathbb{A}_{i,t}} \mathbb{1}_a^k}{|\mathbb{A}_{i,t}|}$$

- ▶ i identifies the establishment
- ▶ k is a 4-digits CPC technology class
- ▶ $K \in \{\text{green, automation}\}$
- ▶ $\mathbb{A}_{i,t}$ the set of ads advertised in establishment i at time t

Instrumenting change in tech adoption: Shift-share IV design (2)

We are interested in the effect of a **change in technology adoption** $\Delta S_{iK,t}$. Following the notation of Borusyak, Hull and Jaravel (2022), for each K , we define a SSIV $z_{iK,t} = \sum_k s_{jk} g_{kt}$:

$$z_{iK,t} = \sum_{k \in K} s_{ik,t_0}^{ads} \ln \left(\sum_{p \in \mathbb{P}_{k,t-\tau}} cw_p \right)$$

- ▶ $\mathbb{P}_{k,t-\tau}$ is the set of patents published in class k in year $t - \tau$
- ▶ cw_p the citation weight of patent p
- ▶ **Exclusion restriction:** we only consider patents \mathbb{P}_k filed **outside the US** in the EPO and JPO (**dyadic patents**)

Estimating equation specification

We consider **long differences** between a baseline period t_0 and an outcome period t_1 :

$$\Delta \log y_{i,t} = \alpha_{t_1} + \Delta S_{iK,t} + \varepsilon_i$$

In practice, in the following results:

- ▶ An **establishment** is defined as a **firm within a commuting zone**
- ▶ Our **baseline** period is **2010 to 2014**
- ▶ Our **outcome** period is **2021 to 2023**
- ▶ The patent set \mathbb{P}_k in the SSIV is accumulated over 2005 to 2015 – implicitly allowing for a 6-year delay between innovation and adoption

Green innovation adoption leads to job creations from 2010 to 2023

$\Delta \log$ in the number of job ads at the establishment level

	(1)	(2)	(3)	(4)
$\Delta \exp.^{green}$	0.390** (0.162)		0.560*** (0.168)	0.544*** (0.170)
$\Delta \exp.^{auto}$		-0.878*** (0.093)	-0.914*** (0.093)	-0.895*** (0.093)
$\Delta \exp.^{green} \times \Delta \exp.^{auto}$				0.674*** (0.246)
Observations	79,678	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
K-P <i>F</i> -stat (green)	690***		391***	361***
K-P <i>F</i> -stat (auto)		2,201***	1,127***	785***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Green innovation is also skills-biased

Δ in the share of high skilled ads at the establishment level

	(1)	(2)	(3)	(4)
$\Delta \text{exp.}^{green}$	0.126*** (0.018)		0.105*** (0.019)	0.102*** (0.018)
$\Delta \text{exp.}^{auto}$		0.117*** (0.011)	0.110*** (0.011)	0.114*** (0.011)
$\Delta \text{exp.}^{green} \times \Delta \text{exp.}^{auto}$				0.152*** (0.032)
Observations	79,678	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
K-P F -stat (green)	690***		391***	361***
K-P F -stat (auto)		2,201***	1,127***	785***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Both green and autom. technology adoption tend to depress wages

$\Delta \log$ in offered salary at the establishment level

	(1)	(2)	(3)	(4)
$\Delta \text{exp.}^{green}$	-0.271** (0.131)		-0.183 (0.134)	-0.186 (0.135)
$\Delta \text{exp.}^{auto}$		-0.324*** (0.084)	-0.308*** (0.084)	-0.316*** (0.084)
$\Delta \text{exp.}^{green} \times \Delta \text{exp.}^{auto}$				-0.436** (0.209)
ΔS_{high}	0.421*** (0.044)	0.355*** (0.043)	0.373*** (0.046)	0.370*** (0.045)
Observations	21,173	21,173	21,173	21,173
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
K-P F -stat (green)	148***		91***	134***
K-P F -stat (auto)		621***	333***	231***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

No evidence of autom. innovation preventing emissions reductions

$\Delta \log$ in CO₂ emissions at the establishment level

	(1)	(2)	(3)	(4)
$\Delta \text{exp.}^{green}$	-0.370*** (0.113)		-0.366*** (0.112)	-0.364*** (0.114)
$\Delta \text{exp.}^{auto}$		0.024 (0.116)	-0.053 (0.134)	-0.042 (0.132)
$\Delta \text{exp.}^{green} \times \Delta \text{exp.}^{auto}$				-0.026 (0.212)
Observations	949	949	949	949
Establishment FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
K-P F -stat (green)	160***		87***	67***
K-P F -stat (auto)		100***	51***	32***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Conclusion

- ▶ **Green innovation's** impact on labor is expected to be **highly heterogeneous**
- ▶ **Green innovation** has become **less labor-augmenting** over time

Preliminary results

- ▶ **Increases** in **green** technology **adoption** leads to **job creations**
- ▶ Evidence that **green innovation** is also **skills-biased**
- ▶ **No evidence** that **automation** adoption **weakens emissions reductions**

Next steps

- ▶ **Heterogeneity** over firm **size, industry, occupation**
- ▶ **Spill-overs** and firm **entry** at the **commuting zone** level

Thank you!

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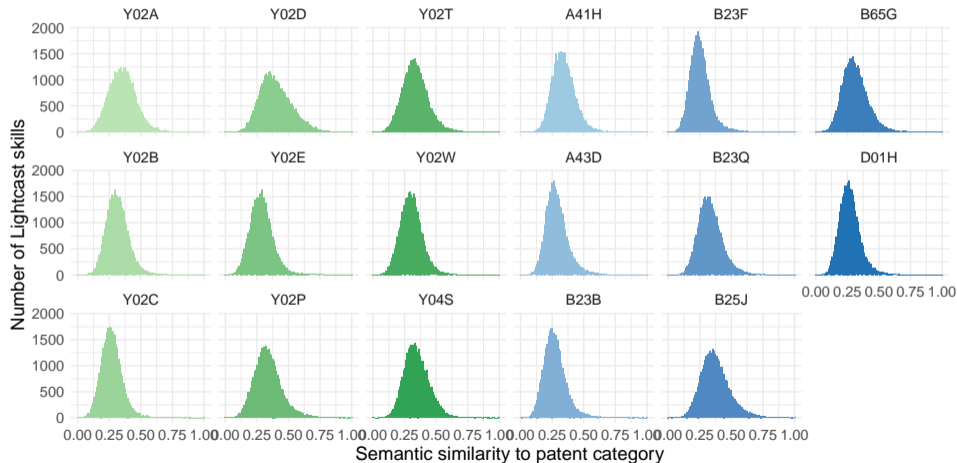
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Linking patents and skills using Sentence Transformers

- ▶ How to **link** between innovation (measured by **patents**) and the skill sets demanded in job openings (measured through **skills**)?
- ▶ **Measure the semantic proximity between CPC code titles and Lightcast skills**
- ▶ We implement **Sentence Transformers** (Reimers & Gurevych, 2019)
 - ▶ Allows to calculate the **semantic proximity** between any two phrases
- ▶ To ensure the vocabulary of the Transformer includes patent-specific terminology, we use **PaECTER** (Ghosh et al., 2024)
 - ▶ Building on Google's BERT for Patents (2020)
 - ▶ Specifically fine-tuned for patent classification on the universe of USPTO patents

Linking patents and skills using Sentence Transformers



Measuring exposure to innovation through **marker skills**

Flood Safety Engineer

- ...
- Hydrology
- **Storm Drains**
- Consulting
- ...

Automation Technician

- ...
- Machinery
- **CNC**
- Leadership
- ...

Sales Technician

- ...
- Selling Techniques
- Driving License
- Sales
- ...

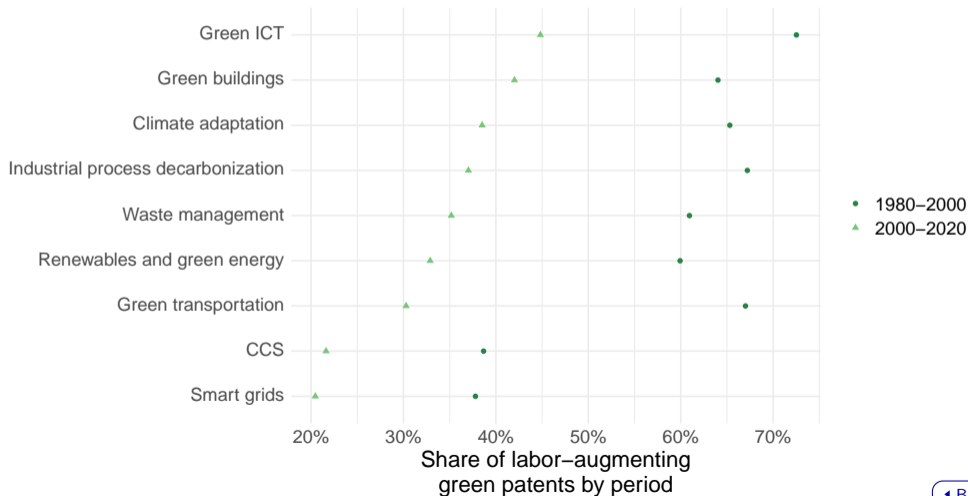
Top marker skills by technology

Y02A – Climate adaptation	Y02B – Green buildings	Y02E – Green energy
Climate Change Adaptation	Energy-Efficient Buildings	Cogeneration
Coastal Management	Energy Efficiency Technologies	Clean Technology
Flood Controls	Residential Energy Efficiency	Carbon Markets
Y02W – Waste management	B23Q – Machine tools	B23B – Turning / Boring
Sewage Sludge Treatment	Machine Tools	Lathes
Wastewater Treatment Plant	Mechanical Assembly	Indexing Head
Solid Waste Management	Rotary Table	Rotary Table

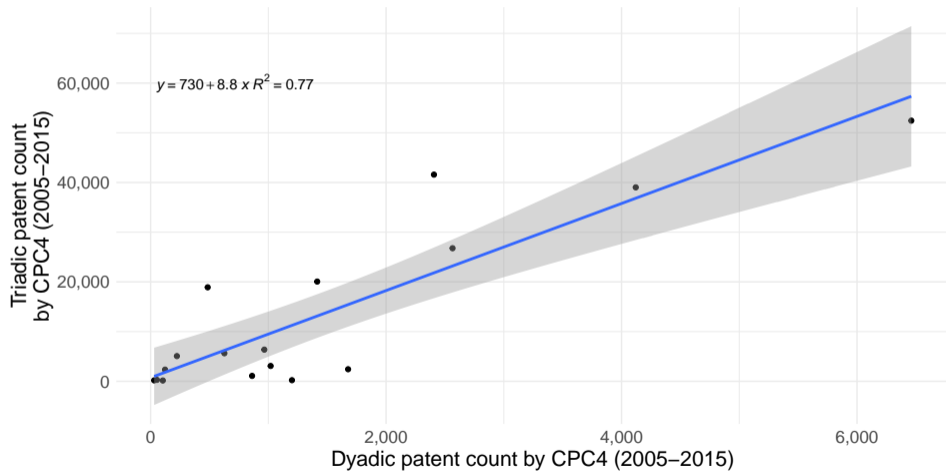
Categorizing green and automation patents using CPC codes

- ▶ **Green** patents:
 - ▶ **Y02: Climate Change Mitigation Technologies**,
 - ▶ Focus on the **technology group** level (**40 technology groups** at 4-digits)
 - ▶ Example of CPC hierarchy:
 - ▶ Y02E Reduction of GHG Emissions, related to energy
 - ▶ **Y02E10/00: Energy generation through renewable energy sources**
 - ▶ Y02E10/50: Photovoltaic energy
 - ▶ Y02E10/546: Polycrystalline silicon PV cells
- ▶ **Automation** patents:
 - ▶ CPC 6-digit codes obtained from Hémous et al. (2024, JPE)
 - ▶ **Automation innovations** that **replace workers** with **equipment** in some tasks
 - ▶ Focus on patents in **machinery**
 - ▶ Two step procedure exploiting **CPC codes**, **keywords** and technology categories

...but decline magnitude has also been heterogeneous



Cumulative flow of triadic vs dyadic patents (2005-2015)



IV: establishment-level ad count, CZ × Period FE (weighted)

Δlog in the number of job ads at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.320** (0.154)		0.451*** (0.157)
$\Delta \text{exp.}^{auto}$		-0.681*** (0.078)	-0.710*** (0.078)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
CZ × Period FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level ad count, NAICS4 × Period FE (weighted)

$\Delta \log$ in the number of job ads at the establishment level

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{exp.}^{green}$	0.203 (0.137)		0.275** (0.139)	0.200 (0.131)		0.260** (0.132)
$\Delta \text{exp.}^{auto}$		-0.452*** (0.076)	-0.464*** (0.076)		-0.376*** (0.067)	-0.387*** (0.067)
Observations	79,678	79,678	79,678	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
CZ × Period FE				Yes	Yes	Yes
NAICS 4-digit × Period FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level salary ratio (weighted)

$\Delta \log$ in offered salary ratio at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	-0.216 (1.159)		0.221 (1.176)
$\Delta \text{exp.}^{auto}$		-2.070*** (0.557)	-2.085*** (0.544)
Observations	5,139	5,139	5,139
K-P F -stat (green)	39***		20***
K-P F -stat (auto)		136***	69***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level ad count (unweighted)

$\Delta \log$ in the number of job ads at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.525*** (0.047)		0.503*** (0.047)
$\Delta \text{exp.}^{auto}$		0.160*** (0.023)	0.129*** (0.024)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F -stat (green)	7,109***		3,619***
K-P F -stat (auto)		10,917***	5,525***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level skills-ratio (unweighted)

$\Delta \log$ in the ratio of high to low skilled ads at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.186*** (0.010)		0.161*** (0.010)
$\Delta \text{exp.}^{auto}$		0.161*** (0.006)	0.151*** (0.006)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F -stat (green)	7,109***		3,619***
K-P F -stat (auto)		10,917***	5,525***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level salary (unweighted)

$\Delta \log$ in offered salary at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.151*** (0.027)		0.171*** (0.028)
$\Delta \text{exp.}^{auto}$		-0.098*** (0.016)	-0.108*** (0.017)
Observations	21,173	21,173	21,173
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F -stat (green)	1,181***		629***
K-P F -stat (auto)		1,857***	942***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level salary ratio (unweighted)

$\Delta \log$ in offered salary ratio at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	-0.249*		-0.251*
	(0.135)		(0.135)
$\Delta \text{exp.}^{auto}$		0.032	0.039
		(0.086)	(0.085)
Observations	5,139	5,139	5,139
K-P F -stat (green)	460***		234***
K-P F -stat (auto)		350***	175***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

IV: establishment-level emissions (weighted)

$\Delta \log$ in CO₂ emissions at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	-0.854 (0.913)		-0.837 (0.906)
$\Delta \text{exp.}^{auto}$		-0.213 (0.605)	-0.053 (0.549)
Observations	949	949	949
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes
K-P F -stat (green)	9***		6***
K-P F -stat (auto)		27***	14***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

OLS: establishment-level ad count (weighted)

$\Delta \log$ in the number of job ads at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.282** (0.114)		0.203* (0.112)
$\Delta \text{exp.}^{auto}$		0.712*** (0.051)	0.704*** (0.051)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

OLS: establishment-level skills-ratio (weighted)

$\Delta \log$ in the ratio of high to low skilled ads at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	0.109*** (0.009)		0.112*** (0.009)
$\Delta \text{exp.}^{auto}$		-0.023*** (0.005)	-0.028*** (0.005)
Observations	79,678	79,678	79,678
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

OLS: establishment-level salary (weighted)

$\Delta \log$ in offered salary at the establishment level

	(1)	(2)	(3)
$\Delta \text{exp.}^{green}$	-0.053 (0.039)		-0.051 (0.039)
$\Delta \text{exp.}^{auto}$		-0.021 (0.026)	-0.018 (0.026)
Observations	21,173	21,173	21,173
Establishment FE	Yes	Yes	Yes
Period FE	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

