The Green and the Dark Side of Occupations, Tasks and Skills

Francesco Vona[1] Giovanni Marin[2]

[1]University of Milan; FEEM
[2]University of Urbino Carlo Bo; SEEDS; FEEM

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Outline of the presentation

Green policies create winners and losers

Distributional effects in the **labour markets** have **large echo** in the **political debate**:

- President Biden: "*When I hear **climate**, I think jobs, **good-paying** union **jobs**... *"
- Congresswoman Bachmann renamed the **Environmental Protection Agency** "*the **job-killing organization** of America.*"
- **Labour market concerns** related to the green transition also in **recent European elections**, e.g. in Germany, the Netherlands, and the UK


Opinion **The FT View**

Europe's green backlash

Rightwing advances in EU parliament elections will lessen climate ambitions

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Green policies create winners and losers (2)

A polarized debate **obscures** the key issues to design **fair green policy packages**:

- *Who are the **winners** and the **losers** in the labour market?*
- *How to ensure a **just transition** for workers and regions left behind?*
- *Which role for **reskilling policies** in creating **self-sustaining local multipliers** and favouring a **smooth labour reallocation**?*
- *How to reconcile **job creation** and **competitiveness** with **green reindustrialization policies**?*
- *Which **LM policies** help increase the **political support** to green policies, especially from the **losers**?*

Identifying winners and losers is challenging

Confusion in the policy debate on the meaning of "green" (Vona, 2021), **two notions** of **"green"** → this confusion applies also to other sectors, such as **climate finance** and **sustainable mobility**:

- **Brown** ("Inverse Green"): Direct pollution-content of occupations, tasks and products.
- **Green**: Technologies that reduce environmental impacts, and the associated occupations and tasks.
    - **Low-carbon**: subset of green tech for de-carbonizing power generation, transport, construction, etc.
- **Neutral** or **gray**: neither green, nor brown, i.e. school teachers, clerks or waiters.

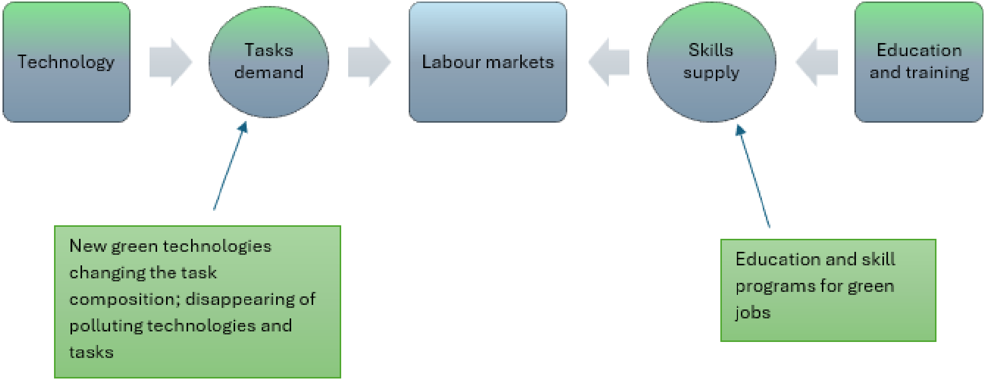
Two metrics needed to understand labour impacts


Concept of green	Exp. Policy effect	Industries	Occupations
Brown (Pollution-content)	job destruction (carbon price)	mining, metals, cement, utilities, etc.	mining engineer, furnace oper., molders, power distributors, etc.
Green (Reducing impacts)	job creation (renew. subsidies)	utilities, construction, machinery, waste manag., transport, etc.	wind technician, roofer, fuel-cell technic., elect. engineer recycling worker, urban planner, etc.

Measuring green jobs

- No data on green jobs **shape** the **debate** in favour of the job killing argument?
- **Green jobs** not in **standard occupational classifications** → to be accurate need to find clever proxies of **exposure** to **green technologies** and **policies**.
- Take advantage of the conceptual framework of the **task model** (Autor et al., 2003; Acemoglu and Autor, 2011; Autor, 2013).
    - **Task**: unit of work that produces output (demand)
    - **Skill**: capability for performing various tasks (supply)

Visual representation of the task model



Data requirements for the task approach to green jobs

- **Granularity of task information** as green occupations are small and **of labour market statistics** (wages, employment) to measure relative performances.
- The **US O*NET's Green Economy program**, combined with BLS LM data, fulfills these requirements. Three categories of **green occupations**
    1. **New green and emerging**: vector of tasks partitioned into green and non-green,
    2. **Green enhanced skills**: vector of tasks partitioned into green and non-green,
    3. **Green demand**/indirectly affected: no info on green tasks, no clear how are identified.
- About 130/1000 **6-digit SOC occupations** belong to the first two categories (roofers, wind turbine technician, regulatory affair specialist).

More on green tasks

- For green occupations, O*NET **partitions** tasks into:
  i. **Green tasks** (climb wind turbine, remove asbestos, monitor legislation on global warming, weatherization)
  ii. **Non-green tasks** (participate in audits, inspect roofs to determine repair procedure, designing and testing aircraft)
- Vona et al. (2018) propose to build a **continuous indicator** of '**greenness**':

$$Greenness_k = \frac{\#\text{ green tasks}_k}{\#\text{ tasks}_k}$$

- The greenness captures the **relative importance** (i.e. **time spent**) on **green tasks** for that occupation (greenness by macro occ.).
- The **EU counterpart** of O*NET, **ESCO**, has a similar partitioning of green and non-green tasks.

How the task and the occupation approach performs?

Context: US, years: 2006-2014.

- **“Binary” occupation-based** definition:

$$Occ - based\ Share_t = \sum_k \mathbb{1}_{k \in green-occ.} \times \frac{L_{kt}}{L_t} \cong \mathbf{11\%}$$

- **Task-based definition** (Vona et al., 2019), reweighting employment shares of occ. k by **greenness** (proxy of time spent in **green activities**):

$$Task - based\ Share_t = \sum_k Greenness_k \times \frac{L_{kt}}{L_t} \cong \mathbf{3\%}$$

- **Cross-validation**: which one is more accurate?
  - Using **green production data**, green share around 2.5% in Europe (Bontadini and Vona, 2023) and just below 2% in the US (Elliott and Lindley, 2017)

Roadmap: what to do without O*NET?

- **Direct proxies** of **green techs** or **policies**,
  - Green production (Frattini et al., 2025), surveys on eco-innovation (Elliott et al., 2024), green patents (Gagliardi et al., 2016), installed capacity (Fabra et al., 2024), stimulus packages (Popp et al., 2021),
  - Pro: technology is what we want to measure through tasks,
  - Con: unable to differentiate green vs non-green tasks, and heterogeneous effects.
- Imputing **O*NET tasks** to other **occupational classifications**:
  - Pro: can be used with **admin data**, such as employee-employer datasets,
  - Con: occupational data often very coarse → **problematic** when **occupations** are **small** as green ones.
  - Con: **time- and context-specific** definitions of what is actually green.
- Use **EU ESCO**, i.e. the recent counterpart of O*NET → preliminary classification of green tasks, but EU-LFS occupational data too coarse.

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Roadmap: what to do without O*NET? (2)

- Use **online job vacancy data** + **ML** or **LLM techniques** to identify green jobs/tasks (Saussay et al., 2022, 2025; Rughi et al., 2025)
  - Pro I: explore **within-occupation** differences btw green and non-green jobs,
  - Pro II: very flexible as **linkable** to specific technologies twin,
  - Pro III: as well as to **specific tasks** and thus occupations,
  - Pro IV: **real-time dynamics** of new work,
  - Con I: **flow** vs. **stock** measures of employment,
  - Con II: **wage offers**, not equilibrium outcomes.

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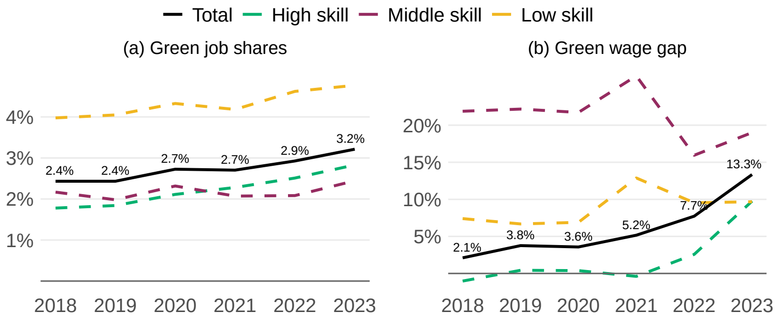
Green job share in different approaches

Measures	Papers	Countries	Share green jobs
Occupation-based	Consoli et al. (2016), Bowen et al. (2018), OECD (2024)	US, Europe	11– ~ 20% (depend if green demand occupations included)
Task-based	Vona et al. (2018, 2019), IMF (2022), JRC (2024)	US, EU	2 – 3% (depending if supplementary tasks considered)
Job-ad-based	Saussay et al. (2022), Cass et al. (2025), Lightcast (2024)	US, EU	US 0.9% only low-carbon, Europe 2.7% (with Denmark outlier)
Job-ad, tech-oriented	Saussay et al. (2025)	US	4 – 5% only low-carbon tech
Green-production based	Elliott and Lindley (2017), Bontadini and Vona (2023)	US, EU	2 – 3% (with Denmark outlier)

Share of green and wage gaps in EU using OJV (Cass et al., ’26)

country plots



Notes. Panel (a) includes EU27 countries plus Norway and Switzerland. Panel (b) includes the 12 countries in the wage regression sample. Weights: country-specific ISCO 3-digit occupation employment.

Measuring green jobs not a goal in itself

But an important first step for policy-relevant analyses of:

- **Skill profiles** of green jobs and impact of **skill mismatches** on job-to-job mobility (see Vona et al., 2018; Saussay et al., 2022; Cass et al., 2025)
- **Indirect job creation** and **local multiplier** effects (see Vona et al., 2019; Popp et al., 2021; Frattini et al., 2025)
- **Labour market impact** of **green technological change** vs. **automation/AI** (see Saussay et al., 2025, later)
- The **attractiveness** of green jobs and the **green wage premium** (see several papers later)
- **Political economy** consequences of the labour market effects of the green transition

Post-green switching effects: empirical framework

- Growing literature on **job displacement effects** in **polluting industries** (Rud et al., 2024; Barreto et al., 2023), but no evidence on the **entry effects** of switching to **fast-growing green occupations**.
- To estimate dynamic impact of switching into green, Kuntze et al. (in-progress) use **linked employer-employee** data for Italy (2011-2019).
  - Treatment: **green core** (resp. **green**) if 4-digit ISCO greenness>0.3 (resp. >0.1),
  - Tackling **endogenous** occupational switching:
    - **stacked DiD** with gray-to-gray (never-treated green) as control group,
    - exact **matching** on gender, region, education dummies, full-time/part-time status and year of switching; caliper matching: age, experience, tenure (2-years bandwidth),
    - controlling for **nonlinear earning dynamics** around the **switching event** that are common to all switchers.

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Raw mean comparisons (1)

Figure: Wages- Green

Figure: Wages- Green Core

Raw mean comparisons (2)

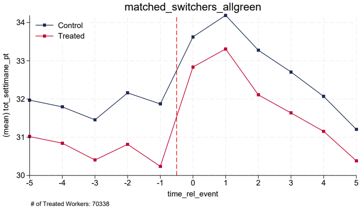

Figure: Weeks- Green

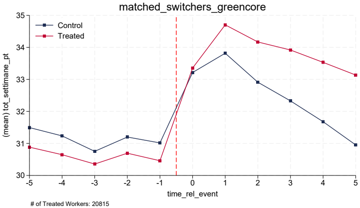

Figure: Weeks- Green Core

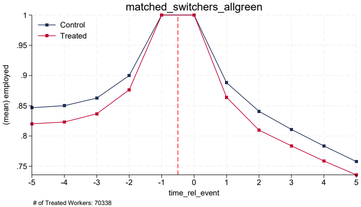

Figure: Employed- Green

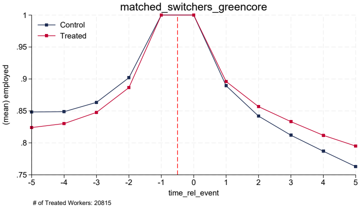

Figure: Employed- Green Core

Dynamic effects of switching into green, cumulative effects

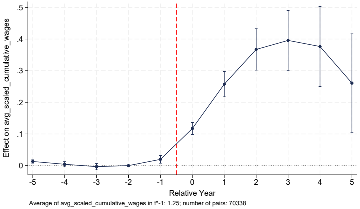

Figure: Wages- Green

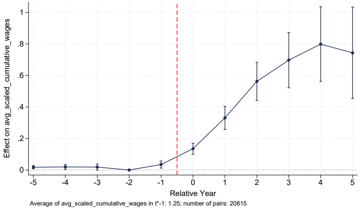

Figure: Wages- Core Green

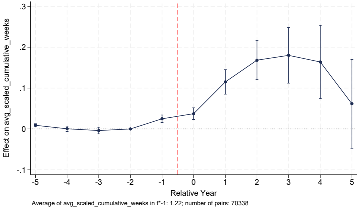

Figure: Weeks- Green

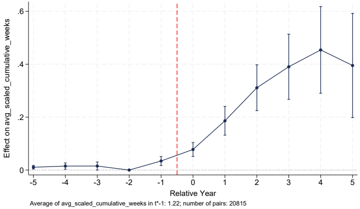

Figure: Weeks- Core Green

Heterogeneous effects

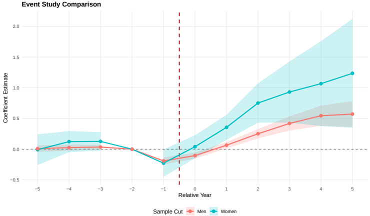

Figure: Wages- by Gender

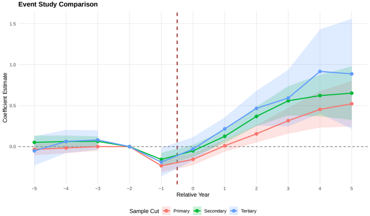

Figure: Wages- by Edu

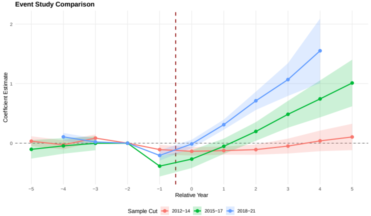

Figure: Wages- by Cohorts

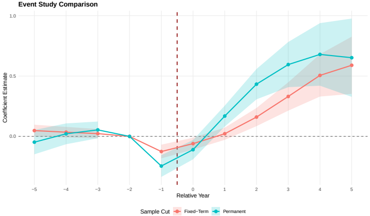

Figure: Wages- by Contract

Consequences for political acceptability

- **Lessons** from the **China shock**: managing the LM distributional effects crucial for **political acceptability** → Are workers correctly perceiving the **potential effects** of the **green transition**? How these translate into **voting behaviour**?
- Cavallotti et al. (2025) explore this issue using ESS data for 14 EU countries (2010-2019).
    - ESS data contains individual-level information on voting and 4-digit level ISCO occupations.
- To mitigate endogeneity concerns, we follow Anelli et al. (2021) computing **greenness** and **browness scores** that are based on a vector of **predicted probabilities** for each individual to be employed in each occupation.

Consequences for political acceptability: material interests are aligned with voting behaviour

Dep. Var.	(1) Green party	(2) Environ score	(3) Environ (broad)	(4) Green party	(5) Environ score	(6) Environ (broad)
Pred greenness	0.473***	2.945***	1.725***			
	(0.126)	(0.579)	(0.624)			
Pred brownness				-0.207***	-1.206***	-0.739**
				(0.057)	(0.276)	(0.305)
Observations	63,496	63,434	63,434	63,496	63,434	63,434
R^2	0.088	0.350	0.400	0.088	0.350	0.400
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Country x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean	0.0731	3.534	2.324	0.0731	3.534	2.324

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

Source: ESS data, Cavallotti et al. (2025)

Consequences for political acceptability (2)

VARIABLES	(1) Green party	(2) Environ	(3) Env (broad)	(4) Green party	(5) Environ	(6) Env (broad)
Pred brownness	-0.543***	-1.051***	-1.524***			
	(0.074)	(0.337)	(0.391)			
Pred brownness × S_r × Δ green patents$_{US,t}$	0.005***	-0.002	0.011***			
	(0.001)	(0.003)	(0.003)			
Pred greenness				0.237*	2.887***	1.196*
				(0.137)	(0.605)	(0.654)
Pred greenness × S_r × Δ green patents$_{US,t}$				0.004***	0.002	0.011**
				(0.001)	(0.003)	(0.004)
Observations	63,334	63,272	63,272	63,334	63,272	63,272
R^2	0.089	0.350	0.400	0.088	0.350	0.400
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Remarks on measurement

Precise measurement of green occupations is **important** not only to provide estimates of the share of green employment.

- Note the difference in the dynamic response after switching of green and core-green occupations.
- In Cavallotti et al. (2025), using a green dummy (e.g., greenness > 0.1 or > 0.3) does not have any effects on voting behaviour.

Carbon-content of occupations (Marin and Vona, 2026)

- **Job vulnerability** to carbon pricing and green policies **beyond coal miners**.
- We build an **index** of the **carbon content of occupations** for 400+ occupations over the period 2003-2019, using **establishment-by-occupation** level data on CO_2 emissions for France:

$$CC_{ot} = \sum_{s=1}^{S} \frac{L_{ost}}{L_{ot}} \times \frac{CO2_{st}}{Y_{st}},$$

  where s indexes 3-digit industry for **manufacturing** sectors (CO2 emissions from EACEI microdata) and 2-digit industries for **non-manufacturing** sectors (CO2 emissions from JRC-Eurostat data)
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Theoretical interpretation of the carbon-content

- The CC of jobs similar to a measure of skill specificity capturing the **carbon-task specificity** $\Rightarrow$ demand of workers specialized in **carbon-intensive** tasks will decline as these tasks are replaced by new green tasks
- **Outside option**: higher carbon content implies **weaker bargaining position** to carbon pricing shocks, but such effect is **unclear** in regulated and non-competitive labour markets
- **Reallocation**, **task reorientation** or **displacement**? We use worker level data to shed light on this issue
  - Key difference with **automation** $\Rightarrow$ are carbon-intensive tasks be replaced by machines? Marin and Vona (2021) show that climate policies **accelerate capital deepening**

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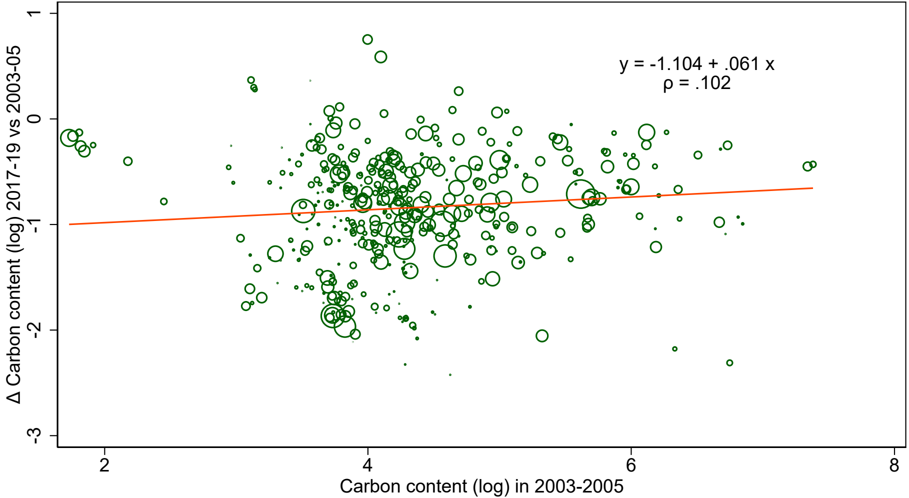
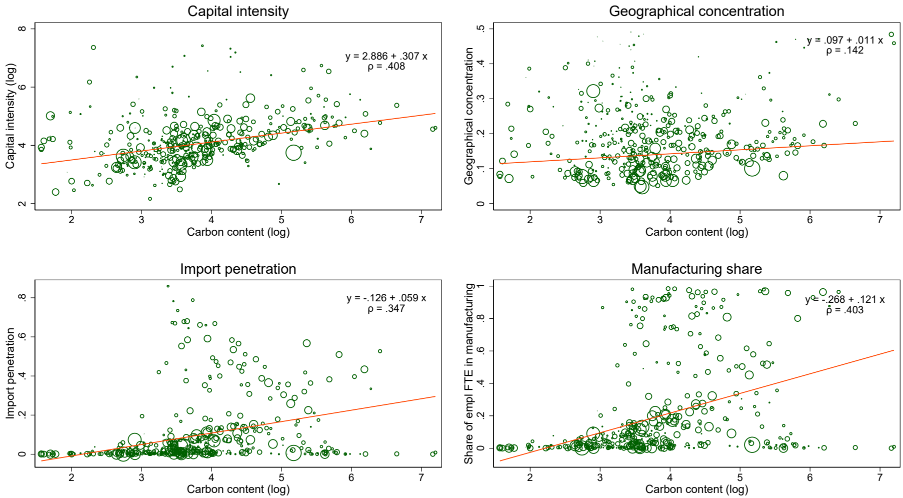
Fact 1: hard-to-decarbonize occupations

transition matrix



Fact 2: carbon-intensive occ. more exposed to other risks



Fact 3: carbon-intensive jobs are concentrated in manual and technical occupations

top/bottom occupations

Occupational group	(1) Mean carbon content	(2) Growth CC, 2017-19 - 2003-05	(3) Std. dev. CC	(4) Employment share
Managers	44.53	-0.504	36.22	0.130
Engineers	77.95	-0.423	150.25	0.092
Admin. jobs	65.61	-0.495	113.19	0.111
Technicians	125.69	-0.471	108.16	0.091
Clerks	53.65	-0.661	134.22	0.251
Skilled manual	116.97	-0.463	112.81	0.259
Unskilled manual	86.36	-0.383	94.37	0.066
Total	81.13	-0.521	1.058	1.000

Notes: Weighted statistics over the years 2003-2019. The weights are the full time equivalent employment of the 4-digit PCS occupation.

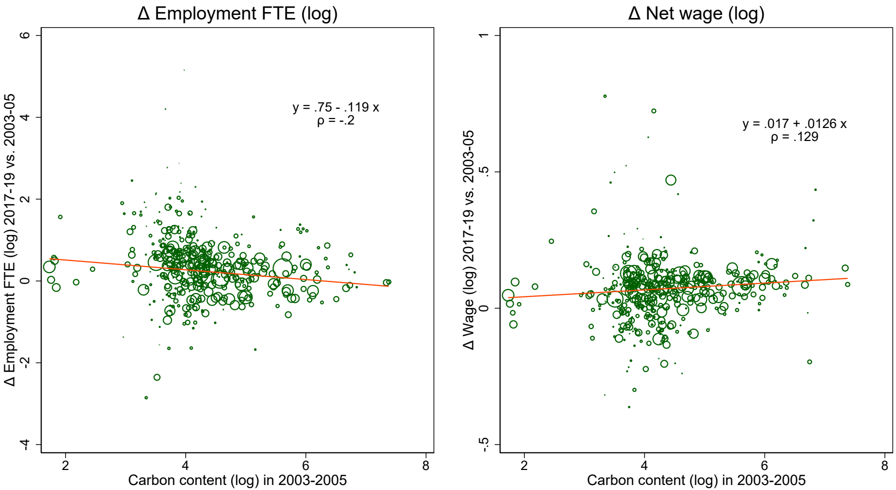
Fact 4: high-carbon workers are primarily old men

Table: Carbon content and demographic characteristics

	(1) Average age	(2) Female share	(3) Change in average age	(4) Change in female share
Carbon content of occupation (log)	1.012***	-0.101***		
	(0.221)	(0.0158)		
Carbon content of occupation (log) in t-1			0.0327***	0.000123
			(0.00985)	(0.000319)
Adjusted R sq	0.0924	0.132	0.0553	0.0127
N of occupations	421	421	421	421
N obs	6953	6953	6548	6548

Notes: Pooled OLS results weighted by occupational employment FTE (in t for columns 1 and 2; in t-1 for columns 3 and 4). Unit of analysis: occupation (4-digit PCS) by year pair. Standard errors clustered by 4-digit PCS occupation in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: year dummies.

Fact 5: employment ↓ in carbon-intensive occ., but wage ≅



Fact 6: workers in carbon intensive occ. are more likely to become not employed, but not to change sector or occupation.

Dep. var.:	(1) Same estab.	(2) New estab.	(3) Not employed	(4) New sector	(5) New occupation	(6) New occ.: ↑ c.c.	(7) New occ.: ↓ c.c.
Carbon content of occ. t-1 (log)	-0.004* (0.0057)	-0.0006 (0.0041)	0.0047* (0.0025)	0.0041 (0.0034)	-0.0089 (0.0056)	-0.057*** (0.0037)	0.0479*** (0.0058)
Adjusted R sq	0.534	0.487	0.637	0.537	0.468	0.573	0.453
N of occupations	421	421	421	421	421	421	421
N obs	6,534	6,534	6,534	6,534	6,534	6,534	6,534

Notes: Regressions are weighted by average workers of the occupation at time $t-1$. Unit of analysis: occupation (4-digit PCS). Standard errors clustered by 4-digit PCS occupation in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. All regressions include year f.e., demographic controls and other occupational controls.

Fact 7: the skills for high-carbon occupations are not that different from green skills

We follow Vona et al. (2018), regressing the importance score of a skill on the log of the occupational carbon content and dummies for 2-digit occupational categories:

$$score^s = \beta log(CC_o) + \mu_{o \in 2-digitPCS} + \epsilon_o,$$

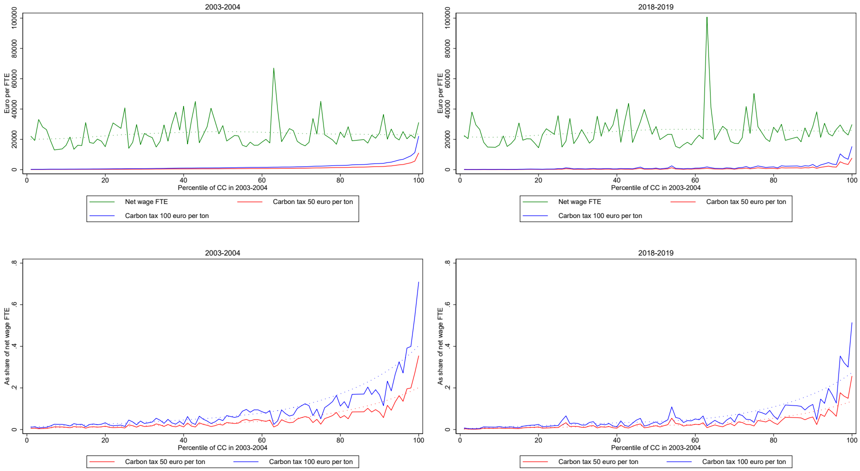
We classify a skill as high-carbon if the β is positive and statistically significance at 95% level of confidence.

Fact 7: the skills for high-carbon occupations are not that different from green skills

Skills	Tasks	Working conditions
Mechanics	Installing	Indoor, non-controlled environment
Technical design	Programming	Outdoor, exposed to climatic conditions
	Quality control	Outdoor, repaired
	Repairing	Indoor, within vehicles or equipments
	Solving unforeseen problems	Exposure to annoying sound or noise
	Maintenance	Exposure to hot and cold temperature
	Monitoring machines	Exposure to pollutants and contaminants
	Equipment control	Importance of controlling machinery

Notes: Our elaboration on Italian ICP and French DADS-Postes data aggregated at PCS 4-digit level. The high-carbon skills listed here are obtained using the methodology proposed by Vona et al. (2018) and discussed in the main text.

Fact 8: large potential impact of carbon tax



Hypothesis: perfect pass-through

Estimating fossil-fuel energy price impacts

We estimate the following equation for an unbalanced panel of **establishment** e**-occupation** o (2- or 4-digit) pairs for the period 2003-2019:

$$
\begin{aligned}
log(Y_{oet}) &= \beta log(P^E_{et}) + \gamma log(CC_{ot}) + \delta log(P^E_{et}) \times log(CC_{ot}) + \alpha_{eo} + \\
&+ \xi_{st} + \phi_{rt} + \rho_{dt} + (\eta_{ot}) + \varepsilon_{oet}
\end{aligned}
$$

where:

- Y_{oet} is the FTE employment/wages
- P^E_{et} is the average price of **dirty energy** in establishment e (properly instrumented)
- CC_{ot}: carbon content of occupation o
- **Favourite** specification controls for **fixed effects**: estab.-occ. (α_{eo}), sector-by-year (ξ_{st}), region-by-year (ϕ_{rt}), initial decile of electr.-by-year (ρ_{dt}) and occupation-by-year (η_{ot}) as well as EU-ETS-by-year dummies

FF prices ↑ accelerate the employment ↓ of high-carbon occ.

Dep. var.: FTE empl. (log, IHS transf.)	(1)	(2)	(3)	(4)	(5)
Carbon content of occ. (log)	-0.130***	-0.130***	-0.099***		-0.0508**
	(0.0344)	(0.0340)	(0.0346)		(0.0364)
FFE price (log)		-0.220	-0.272*	-0.282*	-0.0712
		(0.157)	(0.149)	(0.145)	(0.161)
FFE price (log) x Carbon			-0.180***	-0.360***	-0.151***
cont. of occupations (log)			(0.0499)	(0.0123)	(0.0547)
Occupational classification	2-digit	2-digit	2-digit	2-digit	4-digit
2-dig occ.-by-year dummies	-	-	-	Yes	Yes
F test of excluded IV		91.65	48.11	54.76	49.01
N of establishments	10652	10652	10652	10652	10576
N. obs	995811	995811	995811	995811	4672946

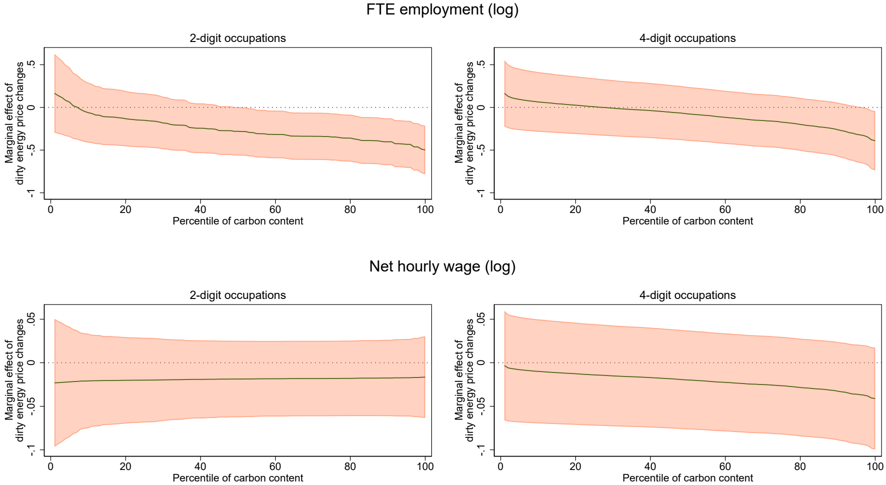
Notes: Instrumental variable estimates (except column 1). Unit of analysis: establishment-occupation (2-digit PCS) pair (establishment-occupation 4-digit PCS in column 5). Standard errors clustered by establishment in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

but again no effects on wages

Dep. var.: hourly net wage (log)	(1)	(2)	(3)	(4)	(5)
Carbon content of occ. (log)	0.0320***	0.0320***	0.0250***		0.00486
	(0.00383)	(0.00385)	(0.00393)		(0.00346)
FFE price (log)		-0.0132	-0.00163	-0.0187	-0.0190
		(0.0242)	(0.0237)	(0.0224)	(0.0290)
FFE price (log) x Carbon cont. of occupations (log)			0.0421***	0.00356	-0.0104
			(0.00803)	(0.0214)	(0.00637)
Occupational classification	2-digit	2-digit	2-digit	2-digit	4-digit
2-dig occ.-by-year dummies	-	-	-	Yes	Yes
F test of excluded IV		92.44	48.61	55.39	46.56
N of establishments	10575	10575	10575	10575	10518
N. obs	702243	702243	702243	702243	1333545

Notes: Instrumental variable estimates (except column 1). Unit of analysis: establishment-occupation (2-digit PCS) pair (establishment-occupation 4-digit PCS in column 5). Standard errors clustered by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Marginal effects



Where high-carbon workers go?

Dep. var.: share employees over total employment (average t, t-1)	(1) Newly hired	(2) Displaced	(3) New establishment	(4) Same establishment	(5) Not employed
FFE price (log)	0.0372	0.0806*	0.0606	-0.090*	0.0199
	(0.0288)	(0.0472)	(0.0444)	(0.0483)	(0.0167)
FFE price (log) x Carbon cont. of occupations (log)	0.0403	0.0548	0.0490*	-0.10**	0.00581
	(0.0352)	(0.0358)	(0.0290)	(0.0419)	(0.0192)
F test of excluded IV	61.41	61.41	61.41	61.41	61.41
N of establishments	10387	10387	10387	10387	10387
N. obs	943627	943627	943627	943627	943627
Net effect: 75th percentile of CC	0.0436	0.0911*	0.0701	-0.109**	0.0211
	(0.0291)	(0.0473)	(0.0441)	(0.0486)	(0.0173)
Net effect: 90th percentile of CC	0.0498	0.0990**	0.0771*	-0.123**	0.0219
	(0.0304)	(0.0481)	(0.0443)	(0.0497)	(0.0182)

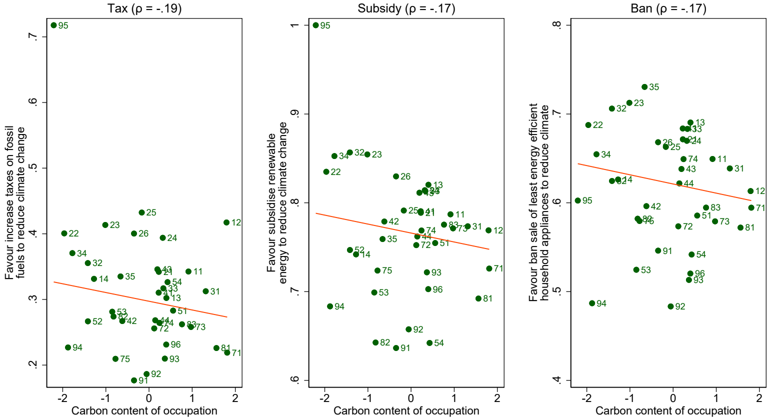
Notes: Instrumental variable estimates. Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clustered by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Where high-carbon workers go? (2)

Dep. var.: share emp./total emp. (average t, t-1)	(6) New occ.	(7) New sector	(8) New occ., new estab.	(9) New occ., same estab.	(10) Same occ., new estab.
FFE price (log)	-0.0318	0.00332	0.0159	-0.0478	0.0432
	(0.0412)	(0.0275)	(0.0135)	(0.0396)	(0.0376)
FFE price (log) x Carbon cont. of occupations (log)	0.00488	-0.0308	0.0186*	-0.0138	0.0281
	(0.0261)	(0.0253)	(0.0113)	(0.0250)	(0.0219)
F test of excluded IV	61.41	61.41	61.41	61.41	61.41
N of establishments	10387	10387	10387	10387	10387
N. obs	943627	943627	943627	943627	943627
Net effect: 75th percentile of CC	-0.0308	-0.00262	0.0195	-0.0505	0.0486
	(0.0417)	(0.0265)	(0.0132)	(0.0403)	(0.0376)
Net effect: 90th percentile of CC	-0.0301	-0.00702	0.0222*	-0.0525	0.0527
	(0.0425)	(0.0263)	(0.0131)	(0.0412)	(0.0379)

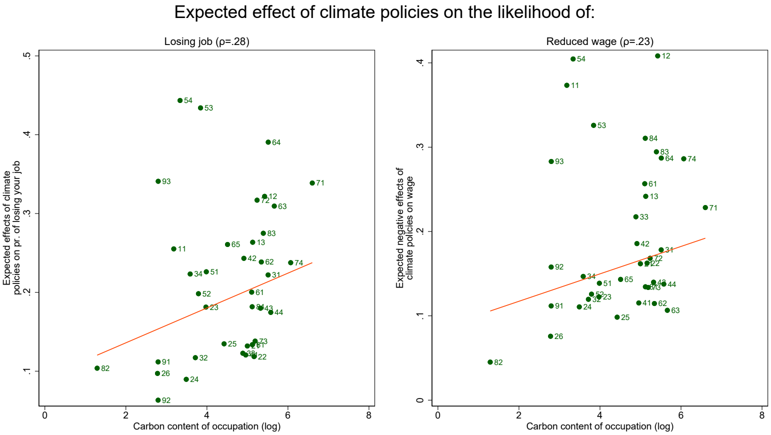
Notes: Instrumental variable estimates. Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clustered by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Additional uses: support to climate policies



European Social Survey (ESS-8) 2016. Data used in De Sario et al. (2023).

Additional uses: perceived vs objective exposure to policies



Survey on a representative sample of 6,500 Italian residents aged 18-80 in June 2025.

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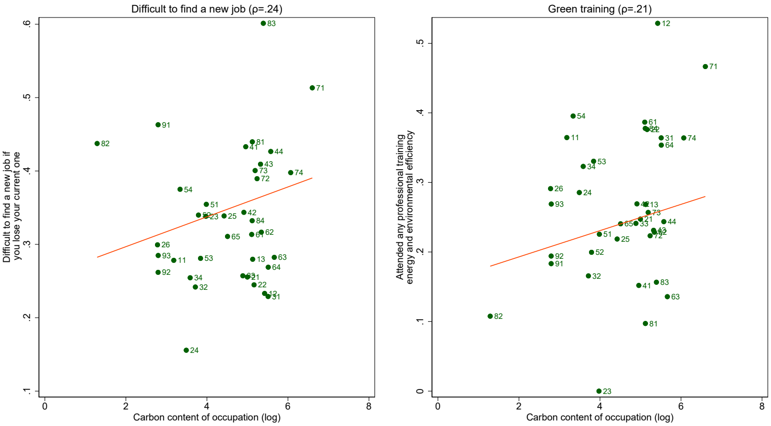

Survey on a representative sample of 6,500 Italian residents aged 18-80 in June 2025.

Suggestions for improvements: measurement

To increase the level of our research, **new measures** of green and brown jobs/skills need to be **transparent**, **well-motivated** and **minimize subjective choices**:

- **Motivation**: Why we need a new measure? Which new aspects allow to uncover?
- **Transparency**: Steps of the algorithm (or of the selection criteria used) as well-documented as possible.
- **Non-subjective**: human adjustments should be minimal, e.g., in deciding if a task or skill is green (example).

Suggestions for improvements: measurement (2)

New measures need to be **cross-validated** and **several strategies** are possible

- **Sensitivity** of the selection to key parameters of the algorithm (especially for OJV-based studies),
- **Test** against other green measures, such as the benchmark of the green task intensity indicator (especially for non-OJV based studies),
- **Check** the share of green and brown jobs against existing estimates and the distribution across macro occupations and sectors.

Some unexplored areas

- Supply of education and skills: *How the educational and training system adapt providing new curricula? How attractive and effective is green education?*,
- Systematic analyses comparing green vs. other technological transitions: *Are green techs more or less labour-saving than automation techs? Which is the impact of the twin transition on labour markets?* (see Saussay's presentation),
- Role of labour market institutions, example of minimum wage floors or unions, and market imperfections → *to assess the limited policy pass-through to workers in both brown (this presentation) and green jobs (Popp et al., 2021)*,
- Nonmonetary attributes of green and brown jobs: *How they affect the wage premia in these occupations?* (see Cass's presentation),
- Mixed evidence on green wage premium: *Need more evidence from admin and matched employer-employee data and for focal workers, such as* STEM.

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THANKS FOR YOUR ATTENTION

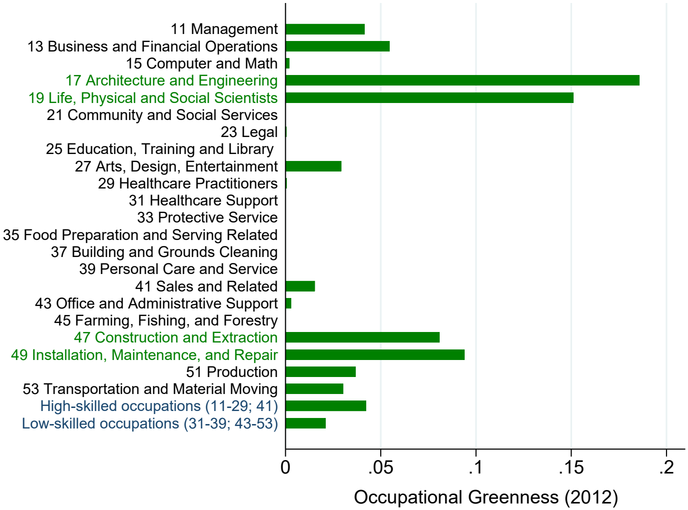
francesco.vona@unimi.it and giovanni.marin@unirb.it

Labour in the Low-Carbon Transition (LiLT), research program at the FEEM and partner of the Grantham Green Skill Lab

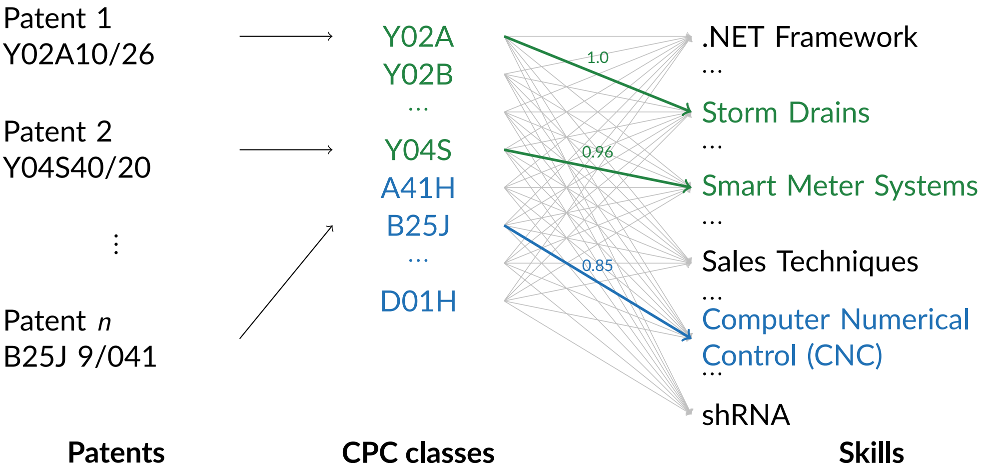
The work presented is joint with:
Davide Consoli (INGENIO),
David Popp (Syracuse University),
Misato Sato and Aurélien Saussay (LSE Grantham),
Leanne Cass (Helsinki University),
Italo Colantone and Piero Stanig (Bocconi),
Federico Frattini and Martino Kuntze (FEEM),
Irene Brunetti and Andrea Ricci (INAPP),
Enrico Cavallotti (EUI),
Layla O'Kane (Emsi Burning Glass).

Green tasks mostly concentrated in 4 occupations

back



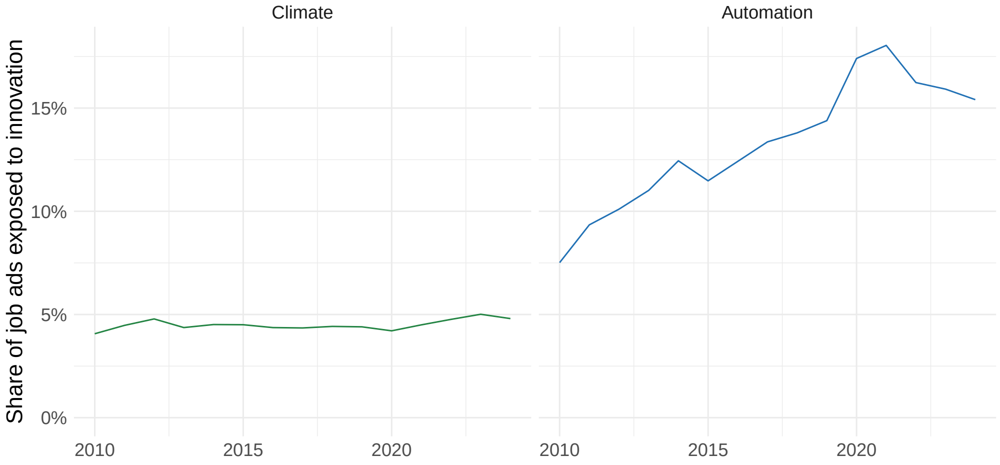
Twin transition: link patent-skill (Saussay et al., in-progress) back



Source: Lightcast data, Saussay et al., in-progress

Share of ads exposed to green and automation technology

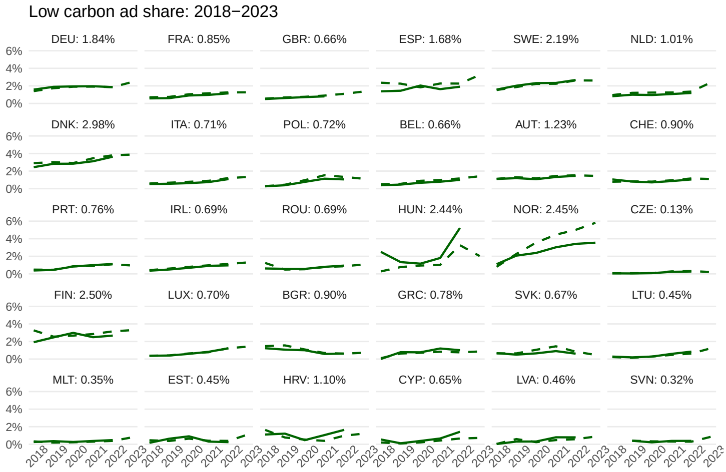
back



Source: Lightcast data, Saussay et al., in-progress

Substantial cross-country heterogeneity

back

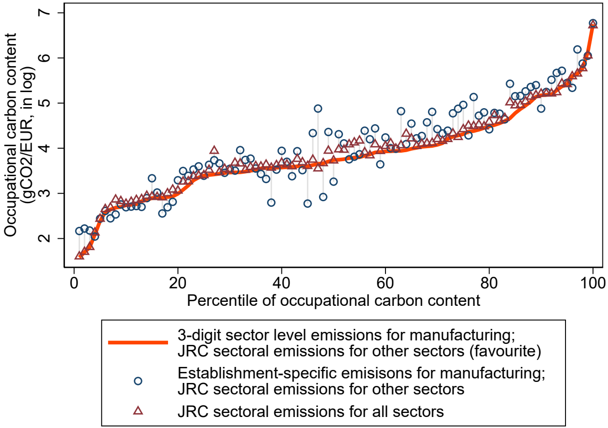


Description of data back

- **Unbalanced panel** of **establishments** for **1996-2019** from **EACEI** (Enquête Annuelle sur le Consommations d'Energie dans l'Industrie), with **unit** of analysis the **establishment**
  - **Survey** on **consumption** and **expenditure** for **energy** products (by **source**: electricity, oil, coal, gas, steam, other)
  - **Stratified sample** of medium-small **manufacturing** establishments (10-250 employees) and universe of big manufacturing establishments (250+ employees)
- We construct a **balanced panel** of 411 occupations (PCS) from **DADS** (Déclaration Annuelle des Données Sociales), with **unit** of analysis the **establishment** (SIRET), only from 2003
  - DADS data **aggregated** from **individual-level** data
  - DADS contains occupational employment (in FTE) and wages for the **universe** of French establishments

Other measures of the carbon content

back



Challenges for the empirical analysis

- **Potential endogeneity** of the **occupational carbon content.**
  - **Occ.-specific carbon content**: use only **sector (3-digit)** CO_2 **intensity** to build a measure of the carbon content of the occupation.
- Interpretation of **energy price as carbon pricing** ⇒ See Marin and Vona (2021): allowing only for contemporaneous effect slightly understates the long-term effect of energy prices.
- **Endogeneity** of energy prices ⇒ three main sources (Marin and Vona, 2021):
  - **quantity discounts**: larger firms pay lower prices
  - unobserved **technological change**: L-E substitution vs. accelerating automation (K replaces both E and L)
  - **anticipated** vs. unanticipated price **shocks**

Instrumental variable back

- We build a shift-share **IV** that **only** keeps **exogenous variations** in energy **prices** and **accounts** for **both sources** of **endogeneity**

$$P_{et}^{IV} = \sum_{f=1}^{F} \phi_{e,t=presample}^{f} P_{t}^{f}$$

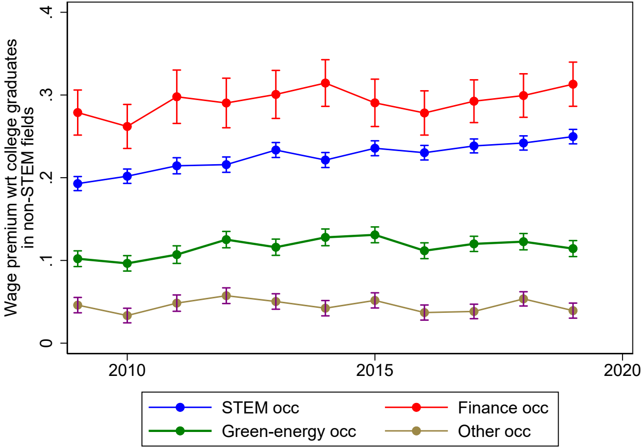
- P_{et}^{IV} **shuts down** endogenous **responses** of establishments to dirty energy prices by weighting price shocks using the **baseline** (lagged) establishment-specific energy mix
- Energy mix observed in the **first year** available in EACEI, **lagged** at least **3 years** from the first observation
- Thus, a Bartik instrument is equivalent to use initial **local shares** (i.e. **energy source shares**) as **instruments** (Goldsmith-Pinkham et al., 2020)
- We test the **parallel trends** assumption with respect to energy source shares

Role of subjective factors in green tasks classification back

- **Context**: reclassify green skills in ESCO using the algorithm proposed by Saussay, Sato, Vona and O'Kane (2022).
- **Policy output**: new tool that can be used by several Public Employment Services (PES) in Europe to guide career consulting and trageting training programs
- **Cross-validate** the selected list of green skills asking PES experts → wide disagreement and heterogeneity on what is a green task
  - 21.4% of **false positives** for Germany vs. just 4.4% for Netherlands
  - Very difficult to be **coherent** within specific sub-domains (e.g., forestry, hazardous waste, ecological research)
  - **Possible solution**: use experts in environmental and climate science, but still scientific disagreement difficult to eliminate

STEM wage premium in green vs. high-skilled occupations

back



source: ACS data, Popp et al. (2024). Here green is low-carbon.

Table: Transition matrix back

Decile (2003) of CC in t-1	1	2	3	4	Decile (2003) of CC in t 5	6	7	8	9	10	Total
1	0.95	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00
2	0.40	0.48	0.10	0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00
3	0.13	0.20	0.59	0.07	0.01	0.00	0.00	0.00	0.00	0.00	1.00
4	0.03	0.02	0.31	0.53	0.09	0.01	0.00	0.00	0.00	0.00	1.00
5	0.04	0.02	0.11	0.36	0.33	0.13	0.00	0.01	0.00	0.00	1.00
6	0.01	0.01	0.02	0.11	0.20	0.56	0.07	0.02	0.00	0.00	1.00
7	0.01	0.00	0.01	0.02	0.01	0.30	0.49	0.14	0.01	0.01	1.00
8	0.00	0.00	0.00	0.00	0.02	0.02	0.17	**0.72**	0.06	0.00	1.00
9	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.17	**0.80**	0.01	1.00
10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.11	**0.88**	1.00
Total	0.50	0.08	0.10	0.06	0.03	0.04	0.03	0.07	0.05	0.03	1.00

Table: List of top/bottom occupations by carbon content in 2019 back

PCS	Description (in French)	CC	% empl
546d	Hôtesses de l'air et stewards	895.9	0.168
389b	Officiers et cadres navigants techniques et commerciaux de l'aviation civile	854.6	0.088
466a	Responsables commerciaux et administratifs des transports de voyageurs et du tourisme (non cadres)	570.7	0.149
637a	Modeleurs, mouleurs-noyauteurs à la main, ouvriers qualifiés du travail du verre ou de la céramique à la main	471.5	0.026
626a	Pilotes d'installation lourde des industries de transformation : métallurgie, production verrière, matériaux de construction	449.6	0.099
389c	Officiers et cadres navigants techniques de la marine marchande	396.1	0.012
626b	Autres opérateurs et ouvriers qualifiés : métallurgie, production verrière, matériaux de construction	388.8	0.555
484b	Agents de maîtrise en fabrication : métallurgie, matériaux lourds et autres industries de transformation	357.0	0.158
386d	Ingénieurs et cadres de la production et de la distribution d'énergie, eau	305.9	0.202
485a	Agents de maîtrise et techniciens en production et distribution d'énergie, eau, chauffage	304.4	0.435
545c	Employés des services techniques des assurances	3.2	0.595
376e	Cadres des services techniques des assurances	3.9	0.434
467c	Professions intermédiaires techniques et commerciales des assurances	4.0	0.396
431e	Sages-femmes (libérales ou salariées)	4.5	<0.001
545d	Employés des services techniques des organismes de sécurité sociale et assimilés	5.4	0.545
564a	Concierges, gardiens d'immeubles	5.4	0.206
467b	Techniciens des opérations bancaires	5.7	0.270
376a	Cadres des marchés financiers	5.7	0.129
376c	Cadres commerciaux de la banque	5.7	0.500
526b	Assistants dentaires, médicaux et vétérinaires, aides de techniciens médicaux	5.7	0.133
	Total	53.7	100

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