Skills for the Green Economy: *What, Where and How Much?*

Francesco Vona,
Senior Economist, OFCE Sciences-Po

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EU Green Deal Plan

- ❖ **Post-pandemic green stimulus**: Next Generation Europe, €750 billion for 2021-2024, and reinforce by the long-term EU budget (€1.1 trillion for 2021-2027) → approximately ¼ allocated to **climate-friendly expenditures**
  - —Low-carbon transport infrastructure and sustainable mobility
  - —New energy grid, storage technologies
  - —Circular economy and new waste management
  - —Building and cleaner construction
  - —Decarbonizing manufacturing
- ❖ The **immaterial infrastructure** is also important: developing **skills** and **competences** required in **emerging green activities**
  - —*Which types of training investments required for the green economy?*
  - —*Who are the workers that require more retraining?*

Skills, central concept

Skills/ tacit knowledge as important as patents/ **codified knowledge**

- Development of green innovations and technology adoption
- Comparative advantage in green productions
- Distributional effects of environmental policies in labour market
- Spatial distributional effects of environmental policies

Outline of the talk

❖ Framework: **task-based approach** to study **green labour markets**

❖ **Four applications**:

— measuring **green employment**
— identifying **green skills**
— effectiveness of **green fiscal push**
— identifying **winners/losers** and estimating **reallocation costs**

❖ **Policy recommendations** and avenues for **future research**

Task-based approach to labour markets
(Autor et al., 2003 QJE; Acemoglu and Autor, 2011 Handb.)

i) **Distinction** between **tasks and skills**

- ❖**Task:** unit of work that produces output (demand)
- ❖**Skill:** capability for performing various tasks (supply)

ii) A set of **complementary tasks** is needed to produce output

iii) **Factors** of production **compete** in **producing each task**

- ❖Computers or robots
- ❖Green/energy-efficient machineries
- ❖Energy and minerals
- ❖Workers with different skills → my focus

iv) **Assignment** of **productive factors, including skills,** to **tasks** is **endogenous**:

- ❖ Relatively cheaper factor used to produce a task
- ❖ Factor costs depend also on policy, e.g. carbon tax for energy

Task-approach and the race between technology and education (Goldin and Katz, 2008 Book; Acemoglu and Autor, 2012 JEL)

- The so-called **race between technology** and **education** can be studied at a **granular level**→ Emerging **mismatches**:
  - The set of tasks change because of technological change, i.e. no coding in old societies.
  - The set of skills adapt to new technologies, i.e. no degrees in computer science.

- **Key issue**: which **institutional mechanisms** enable the formalization and diffusion of practical know-how and new skills (Vona and Consoli, 2015 ICC)?
  - Degree of coordination among actors, types of labour markets, broad features of the educational and training system, i.e. school tracking and centralization/decentralization
  - Types of education and training intervention depend on the type of technology
  - Krueger and Kumar (2004 JME): German apprenticeship system complements specific technologies, but not general purpose ones such as ICTs

Why is this relevant for the green economy?

- Tasks allow for a **granular definition** of **what a green occupation is** → *how prevalent are tasks related to green technologies in a given occupation?*

- Observed **co-occurrences** between **tasks** and **skills** allow to derive a **revealed comparative advantage schedule** → *which skills are important to perform green tasks?*

- **Availability** of the **appropriate skills** → *Is it important to enhance the economic effects of green industrial policies?*

- **Proximity** in the tasks/skills requirement between **green** and **non-green occupations** → *how large training costs will be for displaced workers?*

Application I:
Measuring green employment

Application I: Measuring Green Employment
Vona et al. (2019 JOEG)

- **Difficult to define** what a **green job** is:
  - —General problem of defining also green productions (e.g., filters) and technologies (e.g., biofuels);
  - —Misleading binary definitions, several occupations can be either green or not (e.g., construction workers, electric engineers);

- US **Occupational Information Network** (O*NET), available yearly from 2000:
  - —Very detailed description of the tasks and skills content of +900 occupations;
  - —Tasks: specific to each occupation, with a rich text description attached;
  - —Skills: more than 400, defined for all occupations, with an importance score 1-5;
  - —**Green Economy program**: some **occupations** (~100/900) and **tasks** labeled as **green**

Structure of O*NET data

Demand:
Vector of Occupation-Specific Tasks (vector length varies by occupation)

Green tasks (dichotomous):
- *life-cycle analyses for env. impacts (occ: supply chain manager)*
- *install solar roofing systems (occ: roofer)*
- *perform building weatherization tasks* (occ.: constr. worker)
- design wind farm collector systems (occ: wind energy engineer)
- remove abestos or lead (occ: hazardous material remover)
- apply insulation materials (occ: weatherization installer)

Non-green tasks (dichotomous):
- *negotiate prices and terms with suppliers, vendors (occ.: supply chain manager)*
- *inspect problem roofs to determine the repair procedure (occ.: roofer)*
- *lubricate, clean, or repair machinery, equipment, or tools (occ: constr. worker)*
- participate in internal or external audits (occ: regulatory affair spec.)
- select cartographic elements (occ: geographic information syst. tech.)
- designing, constructing, and testing aircraft (occ: aerospace engineer)
- administer medications to patients and monitor patients (occ.: urse)

Supply:
Vector of General Skills (vector length the same for all occ.)

Work Activities (score 1-5):
- coordinating others
- handling objects

Skills (score 1-5):
-writing
- mathematics

Abilities (score 1-5):
-inductive reasoning
-spatial orientation

Knowledge (score 1-5):
-clerical
- design

Two definitions of green job using O*NET

Two definitions:

1. A **binary definition** of green occupations, what in O*NET are called "**new green"** and "**green enhanced skills"** occupations
2. A **task-based continuous definition**: occupation greenness proportional to the share of green task performed (NB: green tasks defined only for green occupations):

$$Greenness_k = \frac{\#green\ tasks_k}{\#total\ tasks_k}$$

❖ Interpretations of occupational greenness:

—Share of time spent in performing green activities

—Average share of jobs doing green activities

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Two definitions of green job (cnt.)

	Greenness=1	*Greenness* btw 0.5 and 0.3	*Greenness*<0.3
Green Enhanced Occupations	Environmental Engineers, Environ Science Technicians, Hazardous Material Removers	Aerospace Engineers Atmospheric and Space Scientists, Automotive Speciality Technicians, Roofers	Construction Workers, Maintenance & Repair Workers, Inspectors, Marketing Managers
New and Emerging Green Occupations	Wind Energy Engineers, Fuel Cell Technicians, Recycling Coordinators	Electrical Engineering Technologists, Biochemical Engineers, Supply Chain Managers, Precision Agriculture Technicians	Traditional Engineering Occupations, Transportation Planners, Compliance Managers

Aggregate green employment share (GES)

- **Binary occupation-based definition** (Consoli et al., 2016 RP):

$$Binary\ GES_t = \sum_{k=1}^{K} 1_{k \in O*NET\ green} \times \frac{L_{kt}}{L_t} \cong 11\%$$

- **Task-based definition**, reweighting employment shares of occ. k by greenness (Vona et al., 2019 JOEG):

$$Task - based\ GES_t = \sum_{k=1}^{K} Greenness_k \times \frac{L_{kt}}{L_t} \cong 2/3\%$$

- **External validity**: **task-based** approach more in line with other accounts of the green economy
  - —US Green good and service survey ~2% years 2010-2011 (Becker and Shadbegian, 2009 BEJ; Elliott and Lindely, 2017 EE)
  - —Share of green production in German manufact.: 3.3%, 2nd in Europe behind Denmark (Bontadini and Vona, 2020 WP) → prod. share proportional to empl. share

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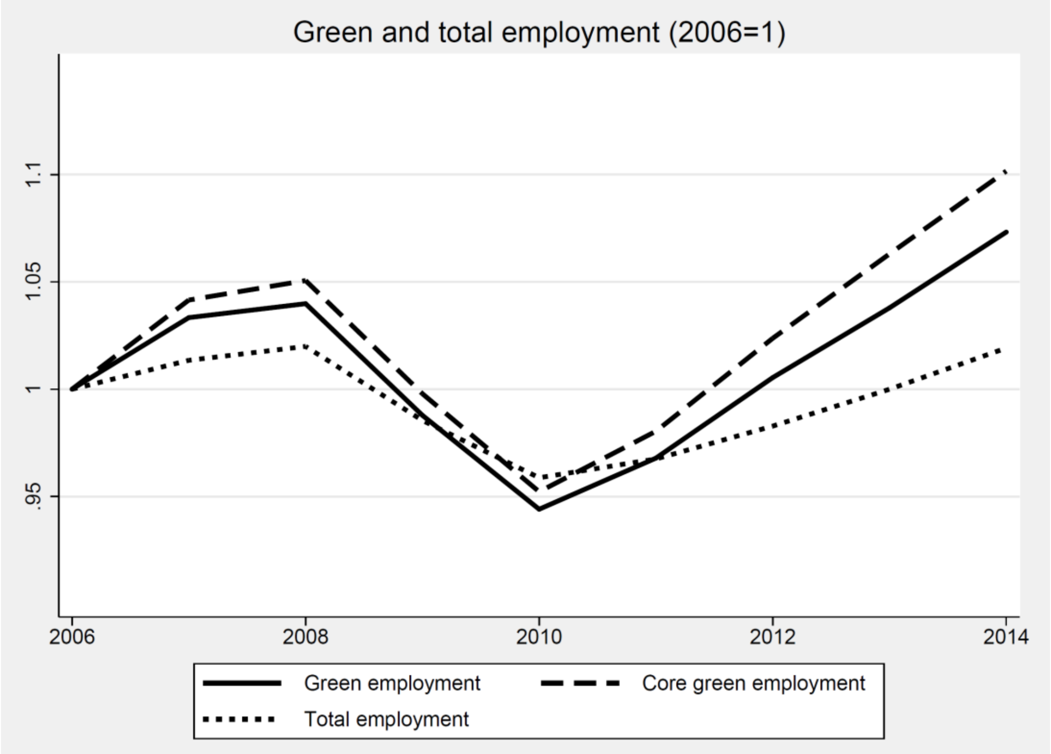
Facts about green employment in US metro areas, 2006-2014

- **Green employment** is more **pro-cyclical** than non-green employment

- **Low-skilled manual green jobs** command a **wage premium of 8%**

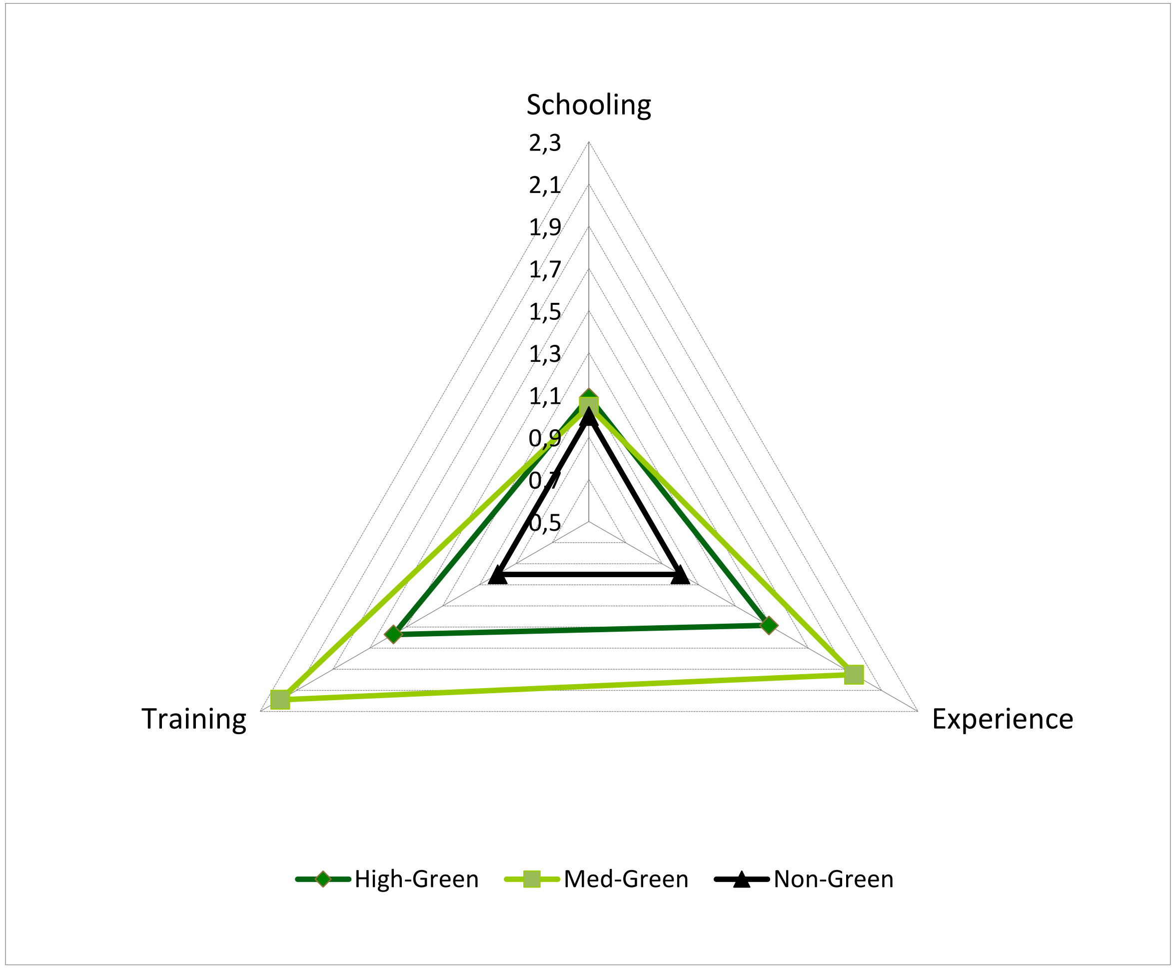
- **Leading green areas** exhibit a strong presence of **high-tech** activities

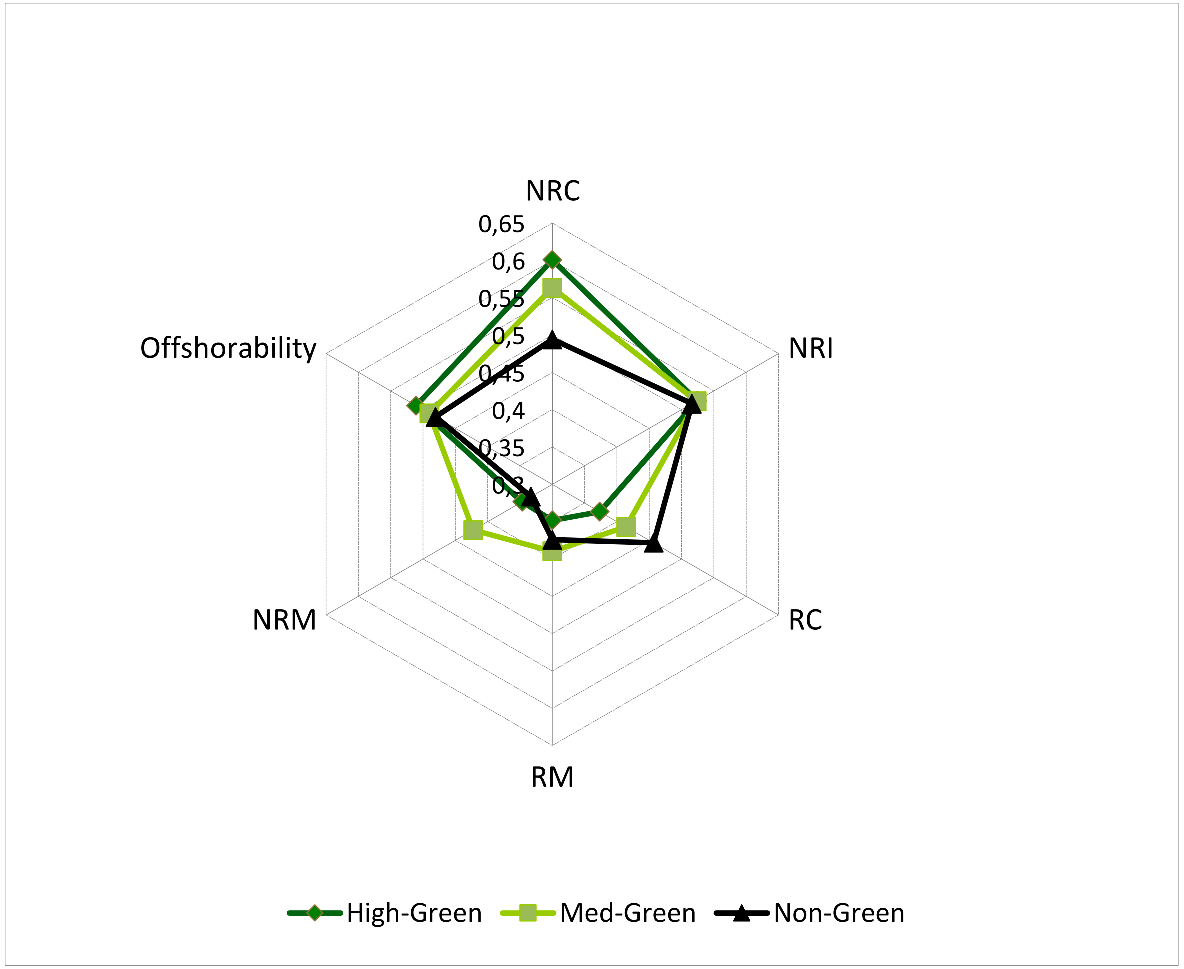
- The **green local job multipliers** is 2 before the great recession and 4 afterwards



Application II:
Identifying Green Skills

Application II: Standard measures of human capital enough to define green skill requirement?





Adapted from Consoli et al. (2016 RP): in the left panel we plot the ratio of human capital measures w.r.t. the average of non-green; in the right panel, we plot the O*NET measures normalized btw 0-1

Application II: identifying green skills
Vona et al. (2018 JAERE)

- The **task-based approach** can be **used** to **identify the skills** that are **important** in **performing green tasks**.

- **Revealed comparative advantage:** we use `greenness' index to select a set of general skills that are particularly relevant for green-intensive occupations:

$$skill\ score_k^s = \beta^s greenness_k + \phi_k^{SOC\_3d} + \varepsilon_k,$$

  - —where 3-digit occupation dummies are added to compare similar occupation and 3-digit occupational groups with no green occupation (e.g., Personal Care and Service) excluded

- A **general skill** is denoted as **green** if $\hat{\beta}^s > 0$ and statistically significant at 1% level. The procedure identifies 16 of such **green general skills (GGS)**

Identifying green skills (cnt.)

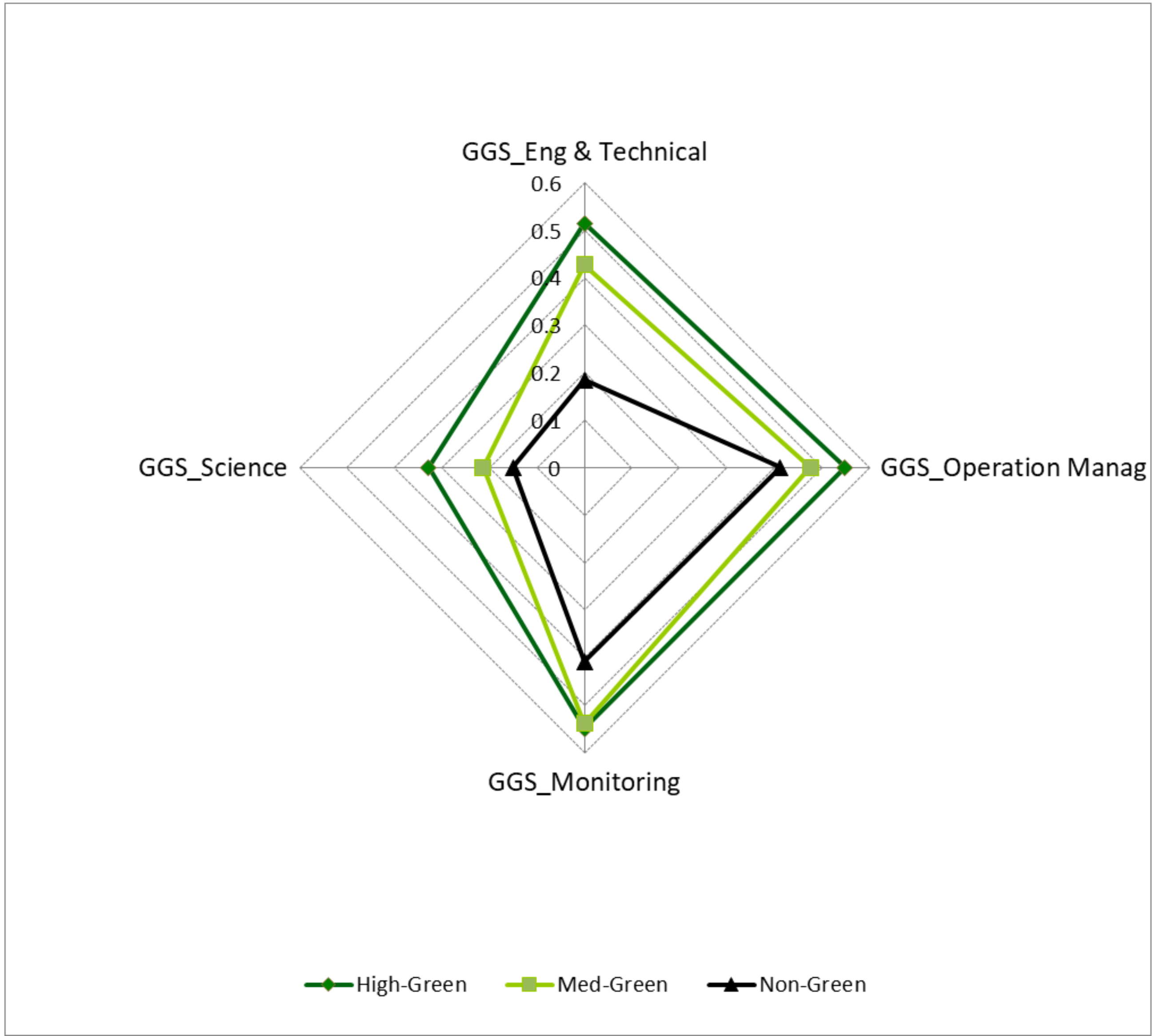
- **Principal component** analysis to **group** and **rank**:

1. *Engineering and technical (34.9% of the skill variance)*
2. *Operation management (24.5% of the skill variance)*
3. *Monitoring (8.2% mostly due to "evaluating information to comply with standards")*
4. *Science (6.2%, only a few science-intensive occupations)*

Table 3. Green General Skills Identified from O*NET

Engineering and technical:	
2C3b	Engineering and Technology
2C3c	Design
2C3d	Building and Construction
2C3e	Mechanical
4A3b2	Drafting, Laying Out, and Specifying Technical Devices, Parts, and Equipment
4A1b3	Estimating the Quantifiable Characteristics of Products, Events, or Information
Operation management:	
2B4g	Systems Analysis
2B4h	Systems Evaluation
4A2b3	Updating and Using Relevant Knowledge
4A4b6	Provide Consultation and Advice to Others
Monitoring:	
2C8b	Law and Government
4A2a3	Evaluating Information to Determine Compliance with Standards
Science:	
2C4b	Physics
2C4d	Biology

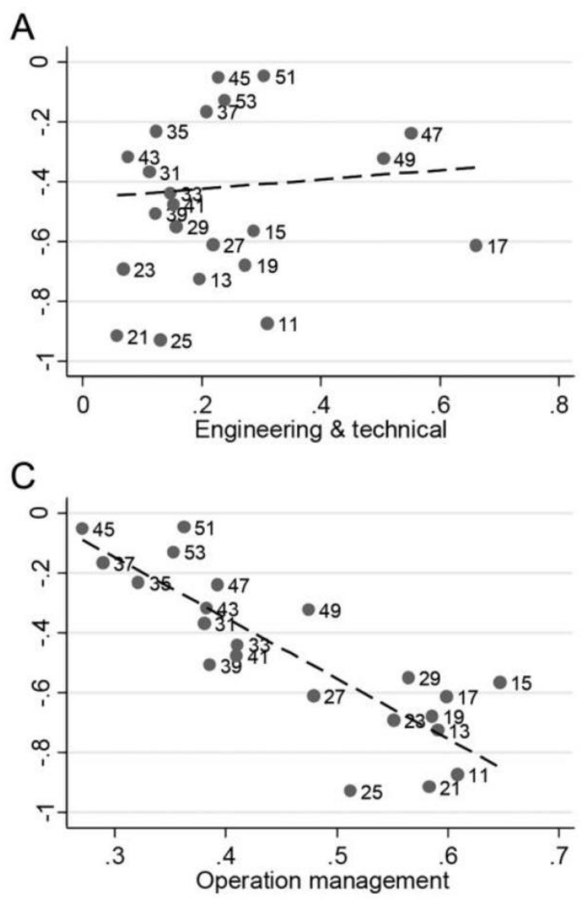
Visualization of Green Skills



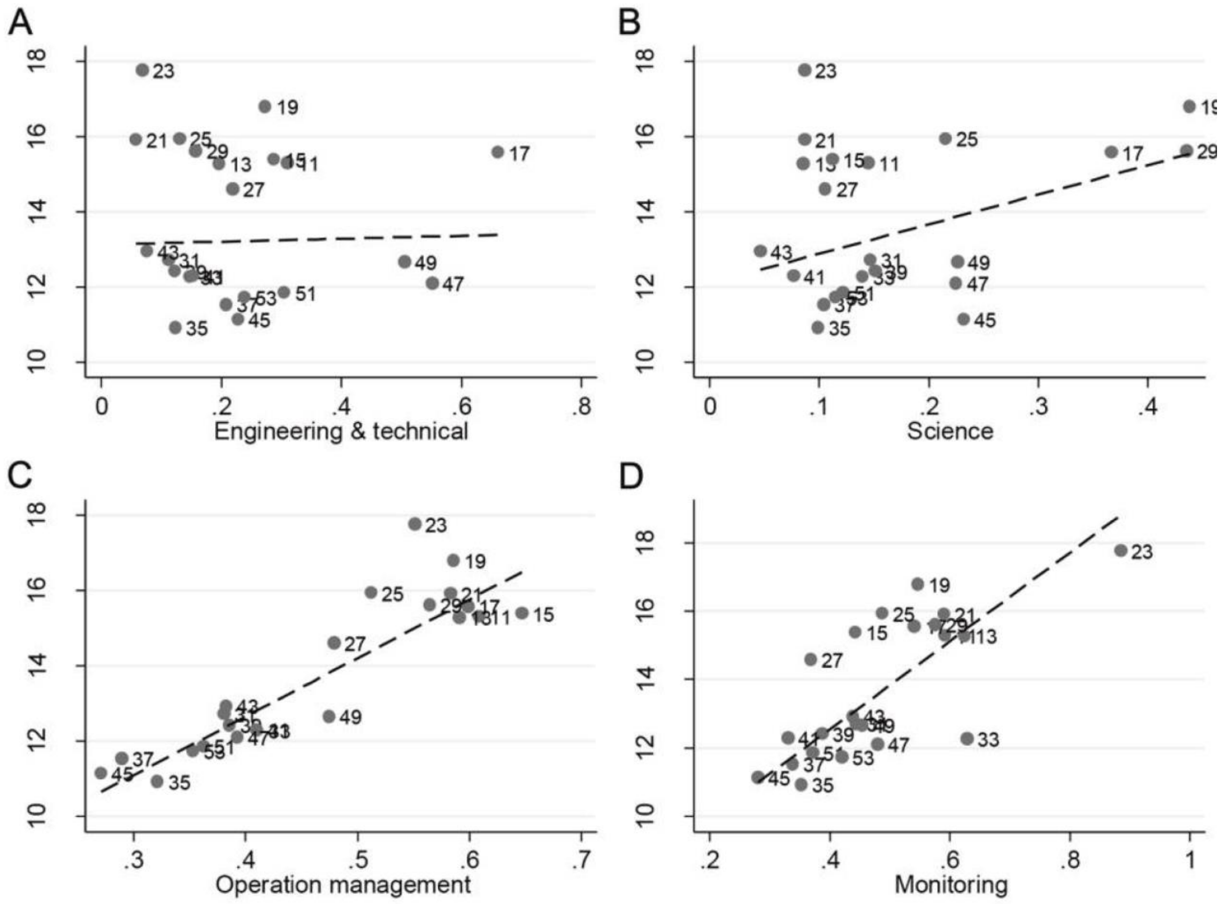
Takeaway → *green skills* are "engineering-type", i.e. strong reliance on experience, heuristics, and integrative forms of practical and technology-specific knowledge → Higher specificity of green skills compared to ICT skills

Correlations with standard human capital measures

Routine-task intensity vs green skills



Years of schooling vs green skills



Notes: weighted by occupational employment shares, source: Vona et al., 2018

Effects of environmental regulation on the demand of green skills

❖ Clean Air Act amendments 2009-11 **research design**:

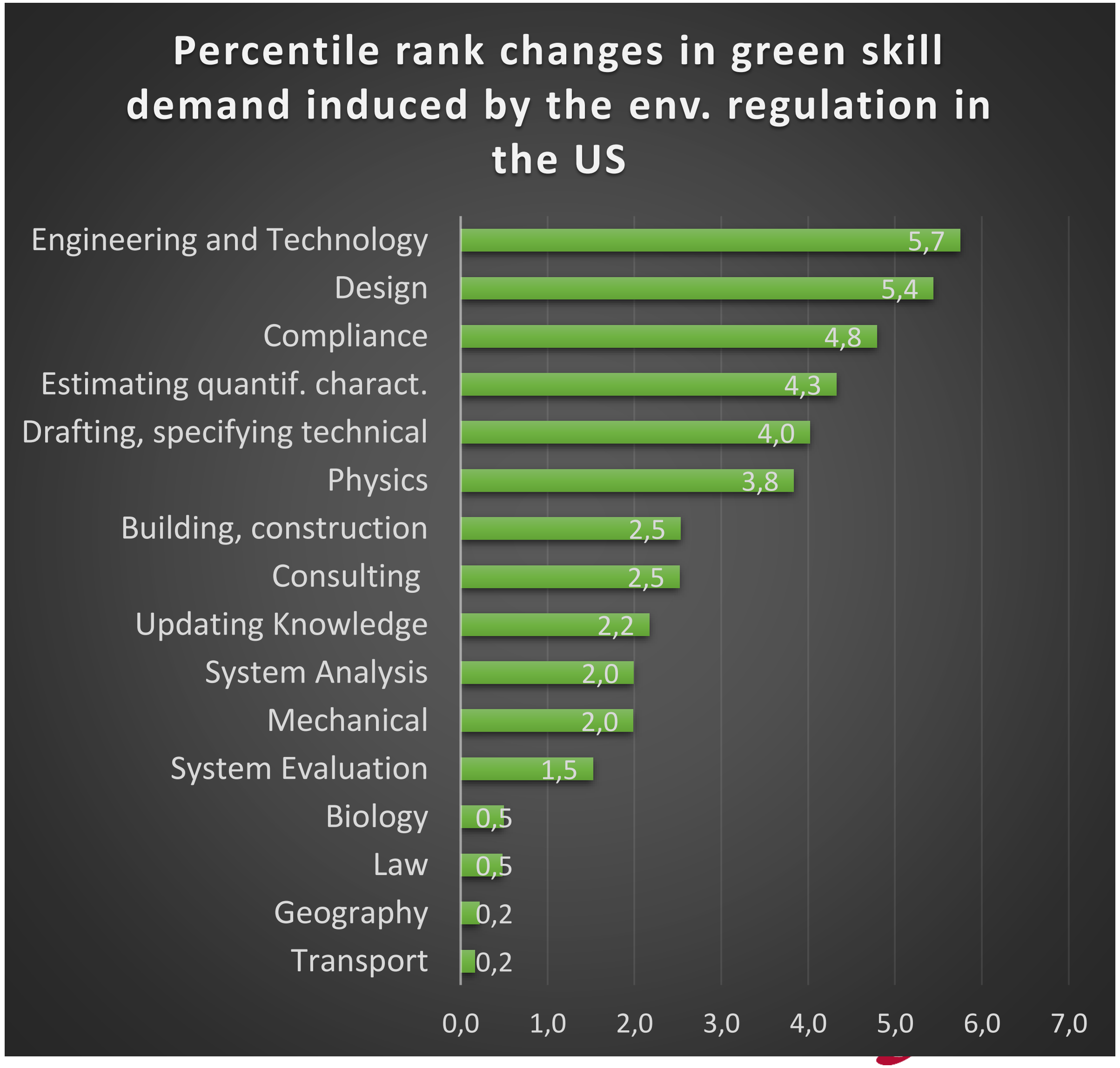
— **Map green skills use (GGS)** to US metro areas j using employment shares:

$$GGS_{jt} = \sum_{k=1}^{K} GGS_k \times \frac{L_{jkt}}{L_{jt}}$$

— Years 2006-2014,

— **Method**: Difference-in-difference + matching estimator + further controlling for exposure to 2008 crisis, trade, etc.

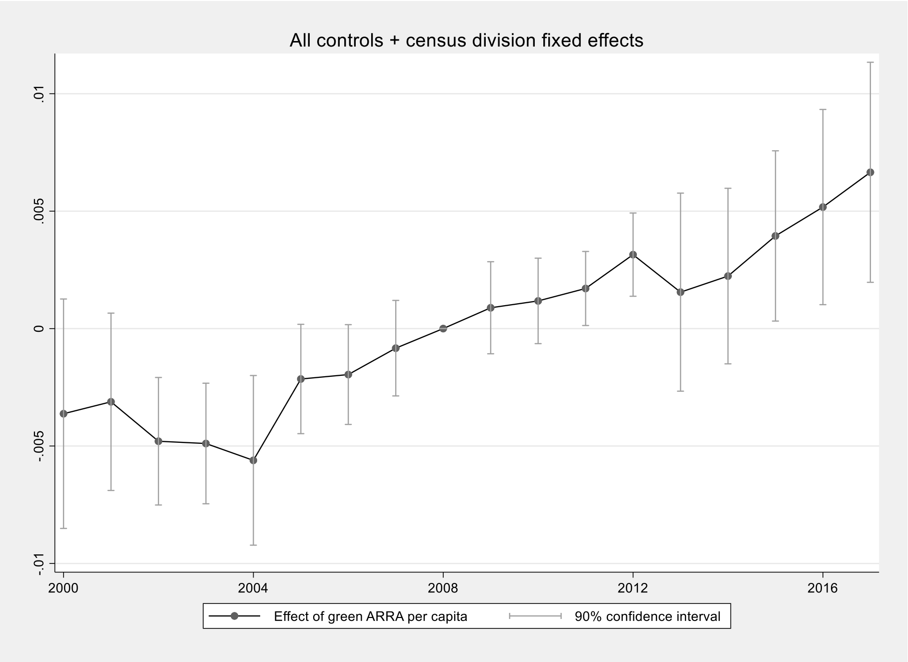
— Results by **skill items**, e.g. ***Engineering & Technical*** = {*design, technology, drafting, mechanical, building, estimating*}



Application III:
Effectiveness of Green Deal Plans

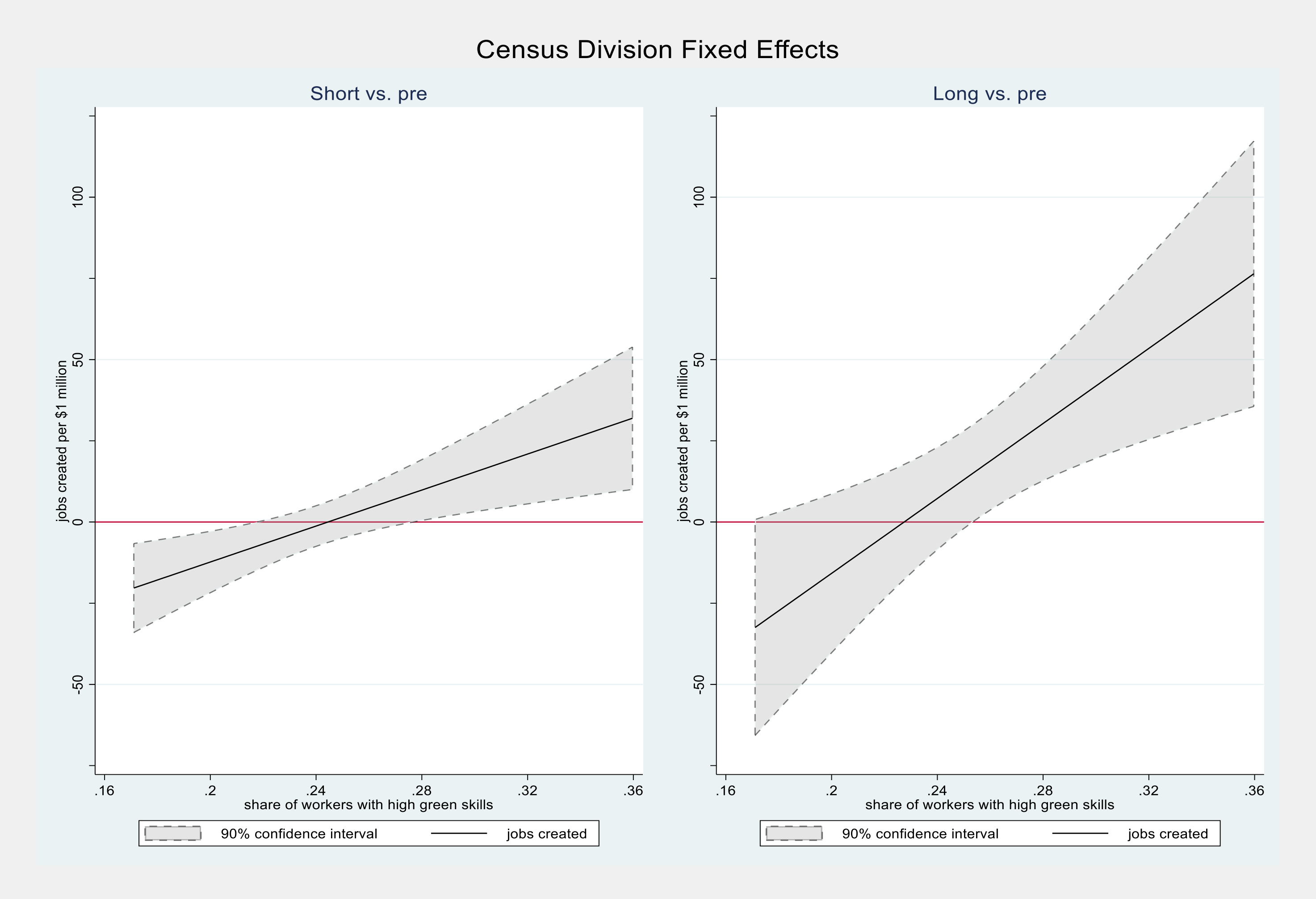
Application III: Effectiveness of Green Deal Plan

- Evaluation of the US **American Recovery and Reinvestment Act** (ARRA) stimulus package (Popp et al., 2020)
  - 17% of grants for the **green economy**: cleanup of polluted sites, energy efficiency retrofits, development of renewable energy resources
- **Method**: Effects estimated **net of pre-trends**, i.e. areas receiving more green spending were growing faster before the financial crisis, and controlling for several intervening factors.



Differently from other components of the ARRA package, effects emerge especially **in the long-run** (10 job x $1 million of green ARRA)
→ Why? One empirically testable explanation is that the availability of the "right" **green skills** played a role

Effectiveness of Green Deal Plan: role of green skills



The net job creation effect **doubled** in regions in the **last quartile** of **green skills distribution**: $1 million of green ARRA created approximately 22 long-run jobs

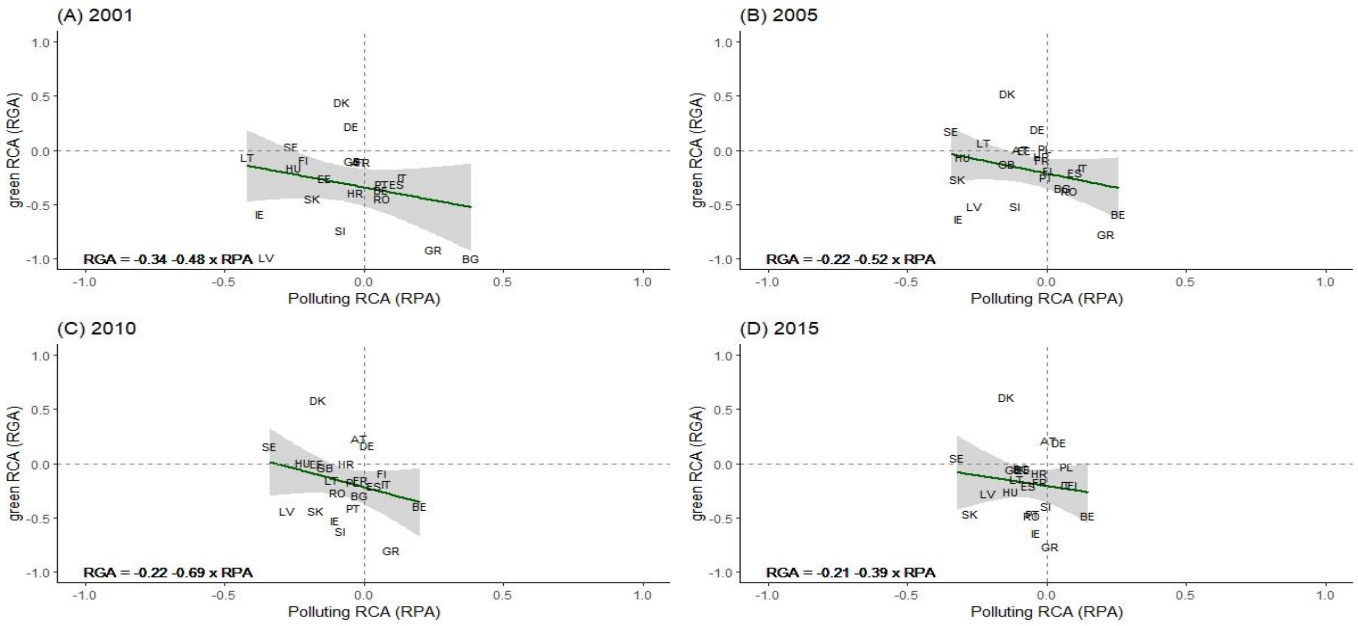
The net job creation effect started to be statistically significant also **in the short-term**

Extrapolation to the EU green deal case?
Bontadini and Vona (2020)

Green deal plan and **regional inequalities**:

❖**Comparative advantage** in **green enabling industries** in a few rich countries (Denmark, Germany, Sweden and Austria), with the appropriate green skills

❖**Comparative advantage** in **polluting industries** in other countries



➢*Will the EU green deal have large distributional effects across countries?*

➢*How to mitigate these distributional effects and to design the Just transition fund?*

Application IV:
Distributional Effects & Reallocation Costs

Application IV: Winners and losers, reallocation costs

- **Job creation** vs. **job destruction** effect what we know:
  - Fact 1: job creation effects concentrated in green jobs and sectors, which do not overlap with polluting sectors with the exception of power generation
  - Fact 2: job destruction effects concentrated in polluting industries and low-skilled manual jobs
  - Fact 3: the reallocation costs depend on skill proximity between green and brown jobs

- More on winners: *We saw that the green deal plan may exacerbate regional inequality, but what about inequalities across workers with different skills?*

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Who are the winners?
(Popp et al., 2020 NBER)

- Effect of the green ARRA on different workers, same empirical strategy as before

Dep var: Change in log employment (by occupational group) per capita compared to 2008	Green employment	Manual occupations	Abstract occupations	Service occupations	Clerical occupations
Green ARRA per capita (log) x pre	0.00001	0.0008	0.0036**	0.0025	0.0040*
	(0.0043)	(0.0027)	(0.0017)	(0.0027)	(0.0022)
Green ARRA per capita (log) x short	0.004	0.0057**	0.0006	-0.0017	-0.0005
	(0.0039)	(0.0022)	(0.002)	(0.0033)	(0.0026)
Green ARRA per capita (log) x long	0.0120**	0.0108**	-0.0017	0.0001	0.0019
	(0.005)	(0.0046)	(0.0044)	(0.0041)	(0.0027)
Jobs created, $1 million green ARRA:					
Short-run - pre-ARRA	0.78	4.7	-4.43	-3.22	-4.69
	(1.49)	(3.39)	(5.12)	(4.16)	(4.75)
Long-run - pre-ARRA	2.66	10.48*	-8.79	-1.99	-2.24
	(1.83)	(5.46)	(8.53)	(4.84)	(4.69)
R squared	0.4159	0.5749	0.5846	0.4747	0.4112
Observations	7631	7631	7631	7631	7631

Employment gains are in manual labor and green occupations, especially in construction

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Who are the losers?
(Marin and Vona, 2019 JEEM)

❖ Digression on **EU countries**:

— Data limitations: No O*NET, we use coarse **occupational categories** from the EU-LFS:
Managers, *Professionals*, *Technicians* and *Manual Workers*

— **Long time span** (1995-2011) and **sector (15)-by-country (14)** analysis

— Environmental policies ~ **energy prices**: market-based instruments

❖ **Research design**:

- Cluster analysis to control in a flexible way for the exposure to **multiple structural transformations**: *automation, trade, etc.*
- **Shift-share instrumental variable** to identify the causal effect of energy prices: isolate the exogenous component of energy price shocks

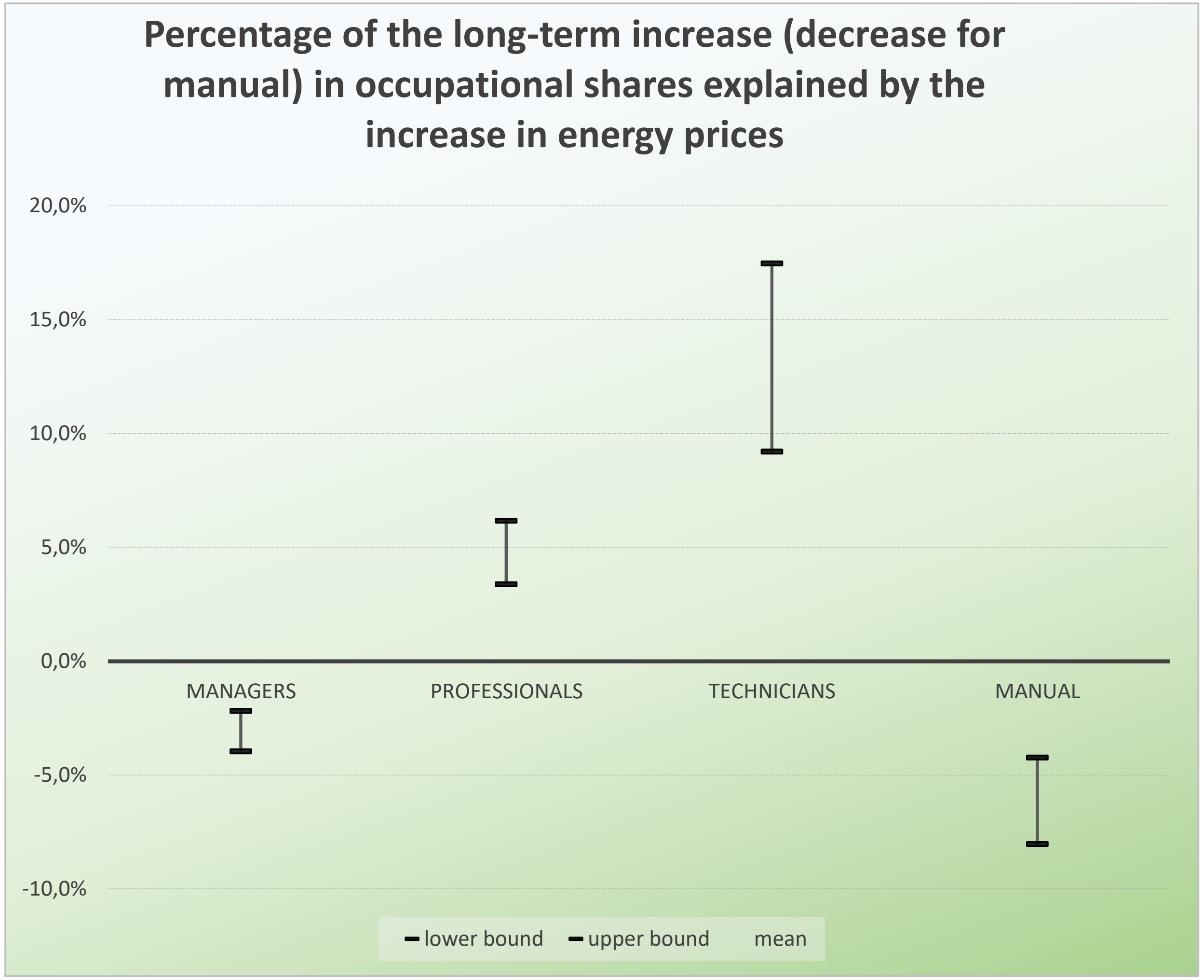
More on the losers (cnt.)

❖ **Long-term changes in energy price** explain:

i. A (often weakly significant) long-term reduction of employment btw -0.9% and -1.6% , in spite of a remarkable increase in energy prices between 1995 and 2011 (i.e. 75%)

ii. Only btw 4.2% and 8.4% of the decline in the **share** of **manual workers**

iii. A 13.3% increase in the share of **technical workers** (and a 4.8% of professionals which include both lawyers and engineers)



Shift-share instrumental variable estimator, controlling for cluster-, sector- and country-specific trends.

Reallocation cost and skill distance

- ❖ **Reallocation costs** and **re-employability** are proportional to the **skill distance** between jobs
  - —E.g.: Kambourov and Manovskii (2009), Gathmann and Schönberg (2010), Guvenen et al. (2020) → skill distance measured on the vector of skills of O*NET type of data

- ❖ Our results suggest **unskilled workers displaced** by **climate policies** in energy intensive sectors (Marin and Vona, 2019 JEEM) may find **new employment opportunities** in sectors related to the **green economy**, such as construction and waste management

- ➢ *What if we want to use green deal plan to re-employ workers structurally displaced by the Covid-19 crisis and by automation in green jobs?*

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Reallocation costs within the group of low-skilled manual workers (US data)

Skill distance between selected groups of occupations	Training requirements (average months)	Education requirements (average)	Green General Skills (average score)	GGS distance wrt growing (2009-2017) green manual occupations	GGS 'Eng & Tech' distance wrt growing (2009-2017) green manual occupations
Growing (2009-2017) green manual occupations (weighted with greenness)	14.4	12.5	0.398	**0.062 (0.043, 0.096)**	**0.051 (0.028, 0.088)**
Brown manual occupations	**11.9**	**12.1**	**0.337**	**0.063 (0.042, 0.097)**	**0.062 (0.036, 0.114)**
Low-skilled occ. with high automation probability (top 10%)	4.4	11.9	0.221	0.152 (0.117, 0.208)	0.186 (0.116, 0.273)
Low-skilled occupations at risk because of COVID	**7.3**	**11.7**	**0.284**	**0.114 (0.074, 0.154)**	**0.123 (0.074, 0.193)**

Skill distances in columns 5-6 calculated as angular separator distances as in Gathmann and Schönberg (2010) using only the 16 GGS

- **Skill distances** lower between green and brown occupations, than between green and Covid-exposed (or automation-exposed) occupations
  - Broader goals of the EU green deal plan, higher reallocation costs?
  - Gender bias in green occupations another barrier

- We **confirm** that **on-the-job training** very important for green occupations, also when looking at low-skilled manual occupations

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Summing up Policy Insights

- **Insight 1**: **task-based approach** reduces measurement error in assessing the size of green labour markets
  → **better indicator** to understand the response of regional labour market to environmental policies.

- **Insight 2**: the methodology proposed by Vona et al. (2018) can be extended to other datasets to identify green skills and training requirements
  → existing evidence emphasizes the importance of **technical** and **vocational** education , Germany institutional setting and training system well-designed for this.

- **Insight 3**: in spite of skill-biased effects, **labour market inequalities induced** by **environmental policies** may not be so large as **winners** and **losers partially overlap**
  → however, **less overlapping** for **large scale green push** targeting workers displaced by the Covid-19 crisis or by automation.
  → **training investments** should be a key part of the EU green deal, to reduce reallocation costs

- **Insight 4**: green policies **may exacerbate regional inequalities**. The winners are regions with a strong technical and engineering know-how
  → designing **just transition fund** to enhance the skills in laggard regions, but also to find new niches in the green economy for those regions using coordinated and coherent industrial policies (i.e. organic food chain in France? Green architecture in Italy? Eco-tourism in Greece?).

Avenues for future research and overcoming data limitations

Labour market distributional effects: task-based model designed for this, much more research needed using worker-level longitudinal data to understand wage effects:

- **German IAB panel** very promising as it contains task measures at the job post level, but need a credible definition of green jobs (e.g., Janser, 2019 WP, proposes one).

- **Other countries**: assumption that task content of occupation is similar to the O*NET ones to identify green jobs cross-walking US SOC and EU ISCO (e.g., Elliott et al., 2021 WP)
  - However, crosswalk big problems: small employment shares of green occupations/imposing uniform weights in the crosswalk leads to very large error
  - Better use rich employer-employee data to study the distributional effects of environmental policies across different workers' groups, e.g. managers vs. manual workers → the task-based model can be used to interpret the results looking at the skill content of these jobs.

Avenues for future research and overcoming data limitations (cnt.)

- **Adjustment in the supply side**: which educational and training programs are required for the green economy?
  - —Working on it for the US where rich data on educational programs are available (Marin, Vona, Popp and Chen, in progress), Europe lags behind in terms of data.
  - —Create a survey to map "green-related" training and educational programs.

- The **frontier** of **job ads** (Saussay, Sato and Vona, in-progress):
  - —Allows to distinguish the skill content at a granular level of aggregation, i.e. researcher can observe a green and a non-green job ad within the same occupation.
  - —Very rich list of tasks and skills as in O*NET, thus it is possible to replicate the analysis of Vona et al. (2018) for different occupations and types of technology, identified through text analysis.

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Thanks for your attention!

Email: francesco.vona@sciencespo.fr

Website: https://sites.google.com/view/francescovona/home

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