The Local Job Multipliers of Green Re-industrialization

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Motivation

- Revival of (green) industrial policy [Rodrik, 2014, Tagliapietra and Veugelers, 2020], which resonates with that of a so-called "big push" [Murphy et al., 1989].
- A key element of this new strategy is to foster green industrial productions and the associated value chains.
- EU governments $\rightarrow$ implement a combination of trade tariffs, local content requirement and industrial subsidies, for example through the Net Zero Industry Act (NZIA)

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- A key element of this new strategy is to foster green industrial productions and the associated value chains.
- EU governments $\rightarrow$ implement a combination of trade tariffs, local content requirement and industrial subsidies, for example through the Net Zero Industry Act (NZIA)
- *Which are the economic payoffs of green industrial policies?*
  - ⋆ Whether or not green industrial policies can create jobs can help to gain political support for the transition [Bergquist et al., 2020, Colantone et al., 2024, Cavallotti et al., 2025].
  - ⋆ Further, green fiscal policies can exacerbate regional inequalities [Popp et al., 2022].

This paper

Research question

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- Studies this RQ across EU NUTS2 regions, over the period 2003-2017.
- Uses a country-industry novel measure of green production and exploits it to compute a measure of regional green penetration.
- Effect on regional employment over active workforce, by aggregate sectors.
- Identifies arguably causal effects by implementing a shift-share design that exploits advancements in green innovation.
- Extends along several dimensions.

Related literature

- Main related literature: Job Multipliers
  - ⋆ Fiscal stimulus [Moretti, 2010, Wilson, 2012, Nakamura and Steinsson, 2014, Chodorow-Reich, 2019].
  - ⋆ Green stimulus [Vona et al., 2019, Popp et al., 2022]
  - ⋆ Energy transition [Fabra et al., 2024, Scheifele and Popp, 2024, Cappa et al., 2024, Chan and Zhou, 2024, Wald et al., 2024]
  - ⋆ Brown sector [Black et al., 2005, Marchand, 2012, Hanson, 2023, Rud et al., 2024]
- Key novelty: estimation of green multipliers associated to an expansion of the manufacturing sector in a longitudinal panel of NUTS2 EU regions.

Conceptual Framework

- This paper can be framed as a test of recent theoretical models revisiting the job creation and destruction effects of new technologies [Acemoglu and Restrepo, 2019, Autor et al., 2022, Gregory et al., 2022].
  - ⋆ New technologies are mainly labour-saving on existing tasks.
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- Employment in green activities requires new tasks [Elliott et al., 2024, Saussay et al., 2022, Vona et al., 2018]. Hence, we can expect a positive multiplier within manufacturing.

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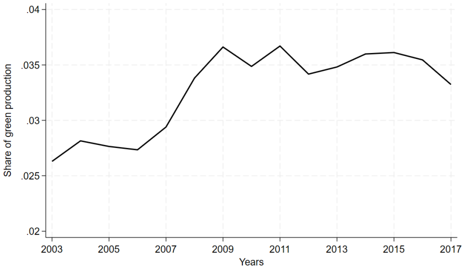
- Employment in green activities requires new tasks [Elliott et al., 2024, Saussay et al., 2022, Vona et al., 2018]. Hence, we can expect a positive multiplier within manufacturing.
- What about outside of manufacturing?
  - ⋆ High and medium-tech activities, such as green ones, pay higher wages that boost local employment through pecuniary externalities [Moretti, 2010].
  - ⋆ Innovative activities, such as green ones, are more likely to attract complementary upstream and downstream activities locally [Lin, 2011, Carlino and Kerr, 2015].
- Hence, we can expect a positive multiplier also outside of manufacturing.

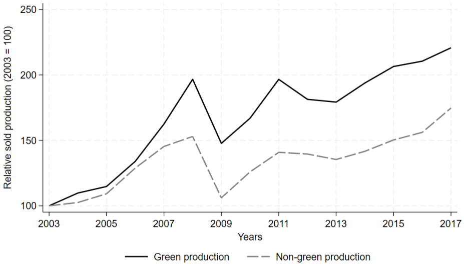
Data sources

- Manufacturing production: PRODCOM (Eurostat). Product-level (8 digits) data on manufacturing production for EU countries (2003-2017).
  - ⋆ Green production: drawing from Bontadini and Vona [2023] we identify a unique list of green manufacturing goods.
- Regional employment: Eurostat. Data on manufacturing (1 and 2 digit) and other sectors (1 digit) at NUTS2 EU region (2003-2017).
- Patents: PATSTAT (1990-2017).
- Demographics: (Eurostat) population, active workforce, share pop. by education, share of foreign citizens at NUTS2 (2003-2017).
- Final dataset is a balanced panel of 278 NUTS2 regions observed from 2003 to 2017.

Green manufacturing production - overtime evolution



(a) share of green production



(b) total and green production

Green manufacturing penetration

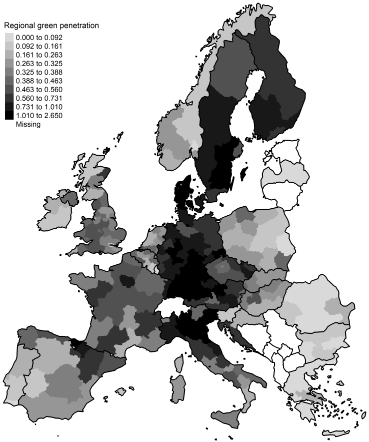
Drawing from Autor et al. [2013] we regionalise (NUTS2) the country-industry green production $\rightarrow$ green manufacturing penetration.

$$GRP_{rt} = \sum_j \frac{L_{rjt}}{L_{cjt}} \cdot \frac{GP_{cjt}}{L_{rt}},$$

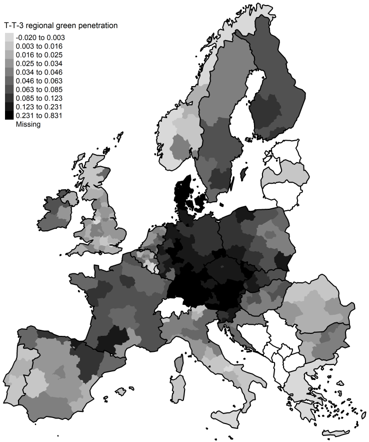
$$\Delta GRP_{rt_k} = \sum_j \frac{L_{rjt-k}}{L_{cjt-k}} \cdot \frac{\Delta GP_{cjt_k}}{L_{rt-k}},$$

- GP_{cjt} is green production in country c, manufacturing industry j at time t.
- $\frac{L_{rjt}}{L_{cjt}}$ are the employment shares of manufacturing industry j in region r and country c at time t.
- ΔGP_{cjt_k} refers to the change of green production in country c, industry j, between t and $t-k$.

Green manufacturing penetration

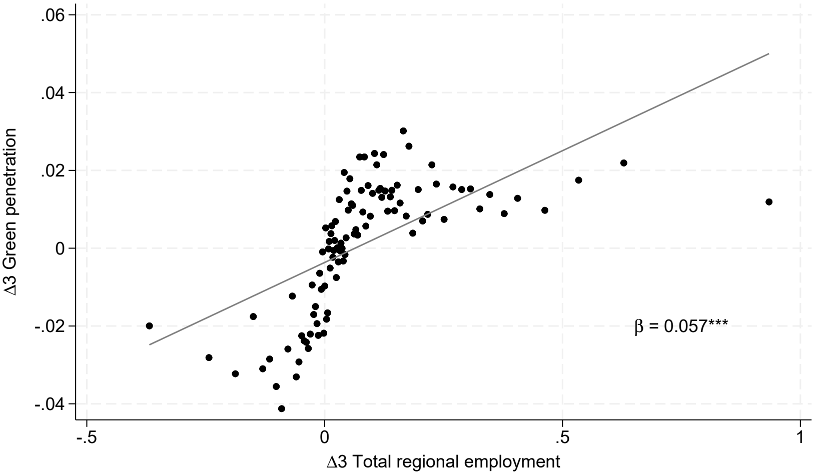


(a) avg. level



(b) avg. 3-years change

Green manufacturing penetration and total regional employment



Identification strategy

- Naively relating regional employment dynamics with green manufacturing penetration likely produces biased estimates.
- We implement a shift-share IV based on green patents. Formally,

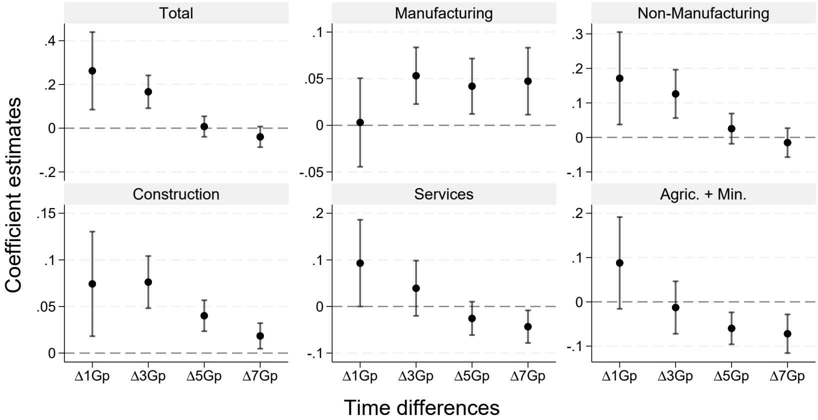
$$\Delta IVGpat_{rt_k} = \sum_j \frac{L_{rj,t_0}}{L_{cjt_0}} \times \frac{\Delta Gpat_{cjt}^{NonEU}}{L_{rt_0}}.$$

- $\frac{L_{rjt_0}}{L_{cjt_0}}$, the share component, are the employment shares of manufacturing industry j in region r and country c at time t_0 (avg. between 2000 and 2003).
- $\Delta Gpat_{cjt}^{NonEU}$, the shift component, is the flow of EPO green patents by non-EU inventors between t and t_k allocated to country-sector pair (c, j).
- Intuition $\rightarrow$ regions with stronger baseline green technological capabilities are able to benefit relatively more from a global green technology push.

Estimating equation - 2SLS

$$\Delta L_{rt_k} = \alpha + \beta \Delta \widehat{GRP_{rt_k}} + \gamma \mathbf{X'}_{rt_0} \times \tau_t + \tau_t + \eta_c + \epsilon_{rt}.$$

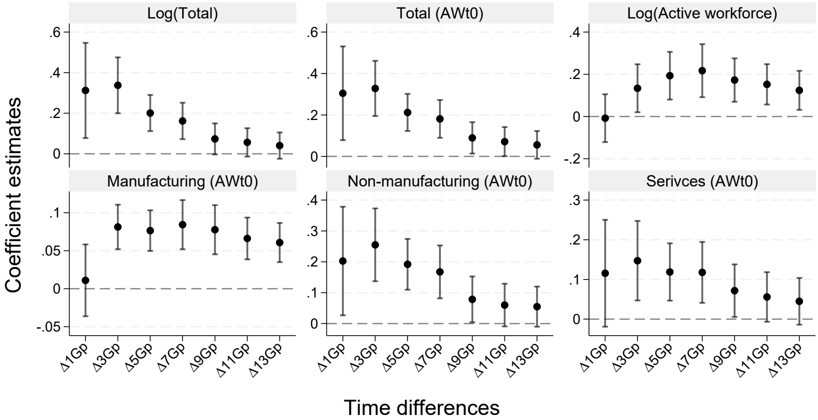
- ΔL_{rt_k} is the change between t and $t-k$ in regional employment over the active workforce.
- ΔGRP_{rt_k} is the predicted change in the green regional penetration per worker.
- τ_t and η_c are time and country dummies.
- $\mathbf{X'}_{rt_0}$ is a vector of key control variables taken at baseline t_0 and interacted with year dummies. These are:
  - ⋆ the share of employment in manufacturing (missing share argument [Borusyak et al., 2021]);
  - ⋆ the non-green regional penetration (size of industrial production in the region).



KP F-Stats: 11.0; 53.4; 140.3; 160.7.
CD F-Stats: 14.9; 79.4; 174.8; 191.8.

3-year change in predicted green manufacturing penetration $\Rightarrow \uparrow \sim$ one tenth of a percentage point in total regional employment.

Main results II



KP F-Stats: 11.0; 53.4; 140.3; 160.7; 129.7; 176.0; 232.5.
CD F-Stats: 14.9; 79.4; 174.8; 191.8; 324.3; 333.9; 234.2.

The negative seven-year effect on total and non-manufacturing employment ⇒ ↑ active work-force ⇒ agglomeration effects.

Identification and Robustness checks

- SSIV validation with Goldsmith-Pinkham et al. [2020]'s machinery. link
  - Identification of 2-digit manufacturing employment shares with the highest Rotemberg weights.
  - Testing the parallel trend assumption.
- Standard IV validation. link
  - Assessing relevance with Lee et al. [2022]'s methodology.
  - Assessing monotonicity assumption.
- Extended controls.
- NUTS1 and NUTS2 fixed effects.
- Regional automation exposure [Anelli et al., 2021].
- NUTS1 clustered standard errors.

Other results

- Investigate the quality of jobs created. $\Rightarrow$ Effects on employment by skill level (low, middle, high and STEM).
  - ⋆ $\Rightarrow \uparrow$ High-skilled and STEM employment benefit the most, while low-skilled to an extent [Popp et al., 2022]. link
- Importance of a just transition in those regions that are specialized in pollution-intensive activities $\Rightarrow$ Effect of green industrialization in brown specialized regions.
  - ⋆ $\Rightarrow$ Polluting intensive regions still benefit from the expansion. link

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- Importance of a just transition in those regions that are specialized in pollution-intensive activities $\Rightarrow$ Effect of green industrialization in brown specialized regions.
  - ⋆ $\Rightarrow$ Polluting intensive regions still benefit from the expansion. link
- Exploit an identification strategy that more closely resembles the case of a "big push" [Murphy et al., 1989] in green industrial policy. $\Rightarrow$ Effect of **large shocks** in green manufacturing penetration.

Large shocks to green manufacturing penetration I

- We implement a staggered DiD that exploits large positive changes to green manufacturing penetration.

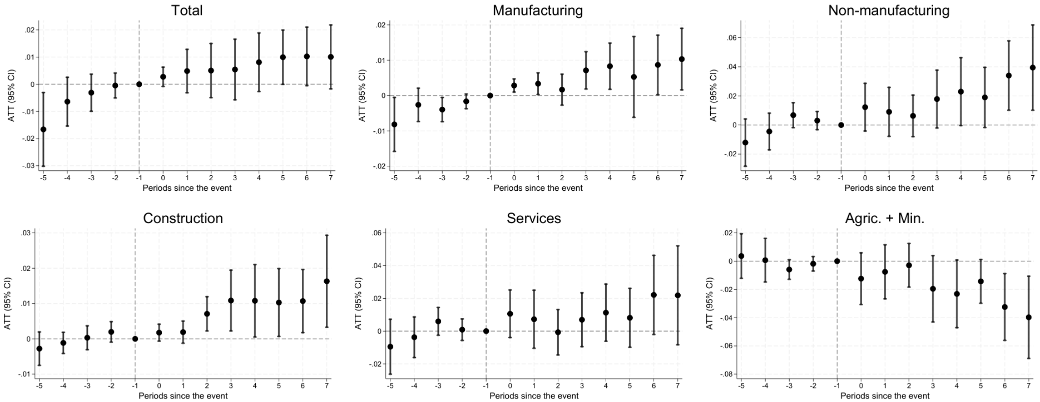
- Intuition → these should proxy for green production related investments [Aghion et al., 2023]. Formally,

$$L_{rt} = \alpha + \sum_{p=-5}^{7} \beta_p GP_{rp} + \gamma \mathbf{X'}_{rt_0} \times \tau_t + \tau_t + \eta_r + \sigma_c \times year + \epsilon_{rt}.$$

- Where $GP_{r,t}$ is a dummy variable equal to 1 if a region r experiences a positive shock in regional green manufacturing penetration between t and $t-1$ above the 90^{th} percentile.

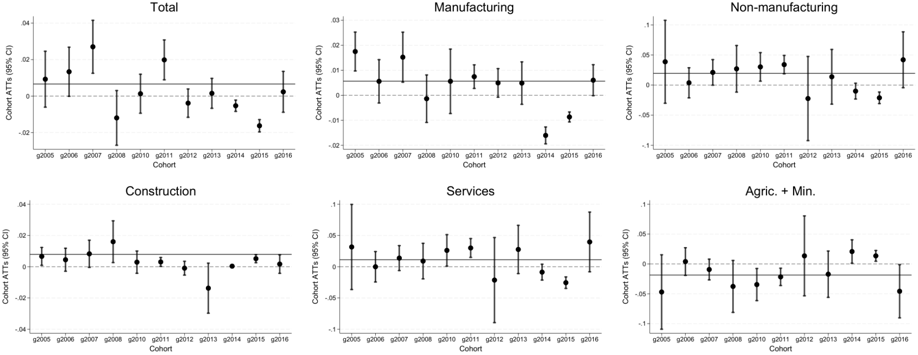
- Given the staggered design, we implement Callaway and Sant'Anna [2021]'s regression adjustment estimator.

Large shocks to green manufacturing penetration II



⇒ Large green shocks have more persistent and larger positive effects on local labour markets.

Large shocks to green manufacturing penetration II



⇒ Most of the effect comes from early treated cohorts. This suggests:

- ⋆ it may be more difficult to reconcile future efforts to promote green industrialization with job creation.
- ⋆ green technologies are becoming more labour-saving.

Conclusions

- Expanding green manufacturing penetration positively impacts employment within and outside manufacturing.
- Such an expansion heterogeneously affects employment by sector [Fabra et al., 2024] and skills [Popp et al., 2022].
- The effects persist when looking at potentially disadvantaged regions.
- The effects persist when employing a different estimation strategy, which yields higher and more persistent effects.

Thank you!

you can find the working paper at:

email: federico.frattini@feem.it
website: https://fedfabfrat.github.io

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SSIV validation I

- Up until recently, identification requirements for shift-share instruments were sort of a "black box".
- Goldsmith-Pinkham et al. [2020] shows that identification can come through the share component, and provide a methodology that allows to understand which are the most important.
- In this context, the share component is identified by the employment shares $\frac{L_{rj,t_0}}{L_{cj,t_0}}$.
- In a nutshell:
  1. Identify the shares with the highest Rotemberg weights (i.e. with 'higher importance').
  2. Run diagnostics test, such as testing for the validity of parallel trends.

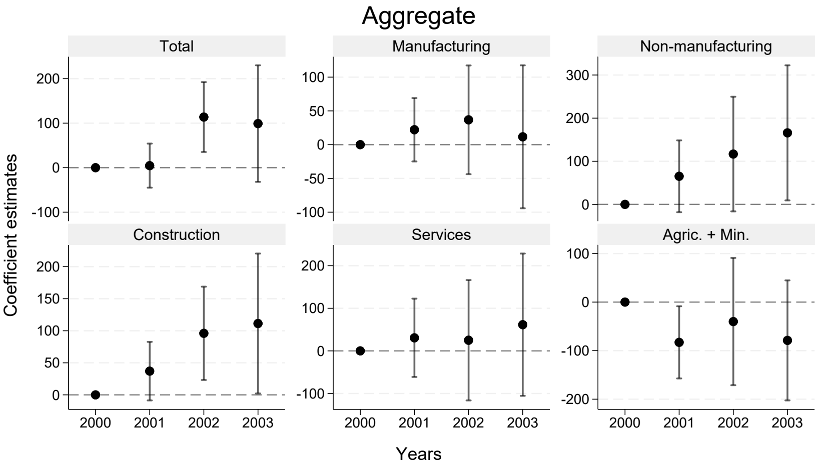
SSIV validation II - Top 5 Rotemberg weights of green patents SSIV

NACE2	Label	Rotemberg weight	Emp. Share (t_0)
28	Manufacture of machinery and equipment n.e.c.	0.301	0.111
27	Manufacture of electrical equipment	0.250	0.109
29	Manufacture of motor vehicles	0.091	0.090
20	Manufacture of chemicals and chemical products	0.066	0.120
26	Manufacture of computer, electronic and optical products	0.063	0.129

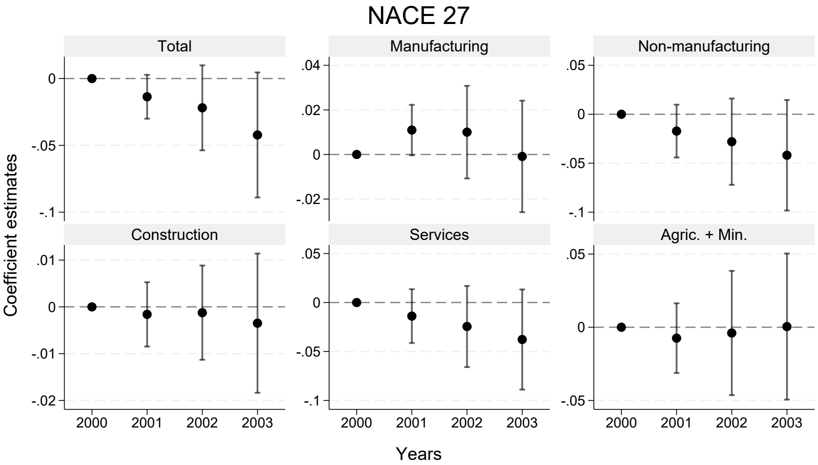
PRODCOM	Label
28211354	Electric furnaces and ovens (excluding induction- and resistance-heated)
28251431	Machinery and apparatus for filtering and purifying gases
28112150	Steam turbines for electricity generation
27201100	Primary cells and primary batteries
27902060	Light-emitting diodes (LEDs)
27112680	Photovoltaic AC generators
29102450	Motor vehicles, with only electric motor for propulsion
29102430	Motor vehicles, with hybrid propulsion
29104313	Road tractors for semi-trailers with only electric motor for propulsion
20595997	Biofuels (diesel substitute)
26517015	Electronic thermostats
26515313	Electronic gas or smoke analysers
26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus

Notes. This table reports 2-digit manufacturing sectors with the highest five Rotember weights associated to the green patents-SSIV [Goldsmith-Pinkham et al., 2020]. Further, it reports the baseline (avg. 2000-2003) employment share within manufacturing of these sectors. Lastly, it reports example of green goods that fall within these sectors.

SSIV validation IV

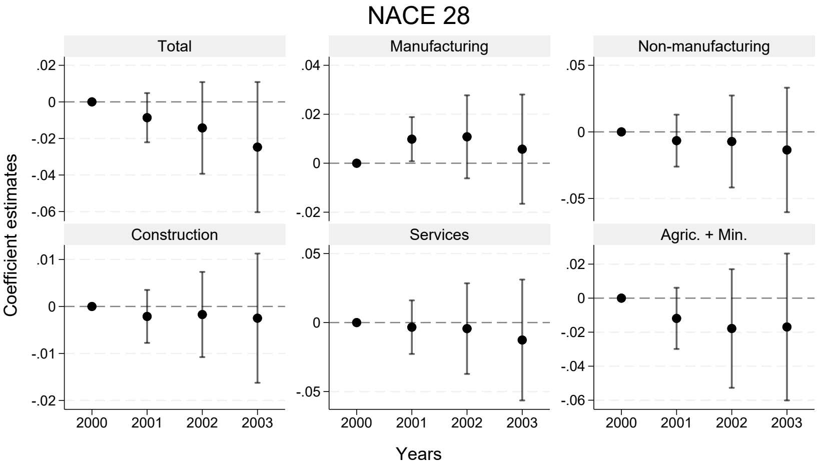


SSIV validation V



SSIV validation VI

back



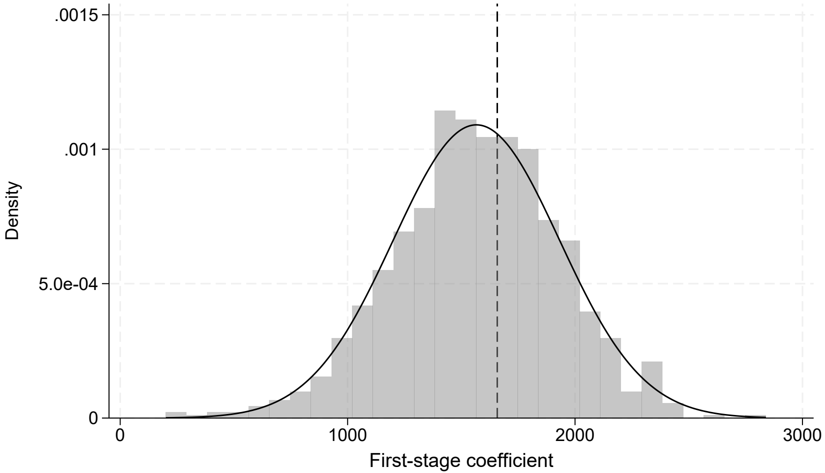
IV validation: relevance [Lee et al., 2022]

Panel A:	*Total*	*Manufacturing*	*Non-manufacturing*
Coefficient	0.166	0.053	0.126
Unadj SE	0.028	0.012	0.046
1% CV of |t|	3.138	3.138	3.138
Adj SE	0.034	0.015	0.056
Adj UB	0.255	0.091	0.269
Adj LB	0.078	0.015	-0.017
FS F-stat	80.909	80.909	80.909
Panel B:	*Construction*	*Services*	*Agric. + Min.*
Coefficient	0.076	0.039	-0.013
Unadj SE	0.012	0.042	0.042
1% CV of |t|	3.138	3.138	3.138
Adj SE	0.015	0.051	0.052
Adj UB	0.115	0.171	0.12
Adj LB	0.038	-0.093	-0.146
FS F-stat	80.909	80.909	80.909

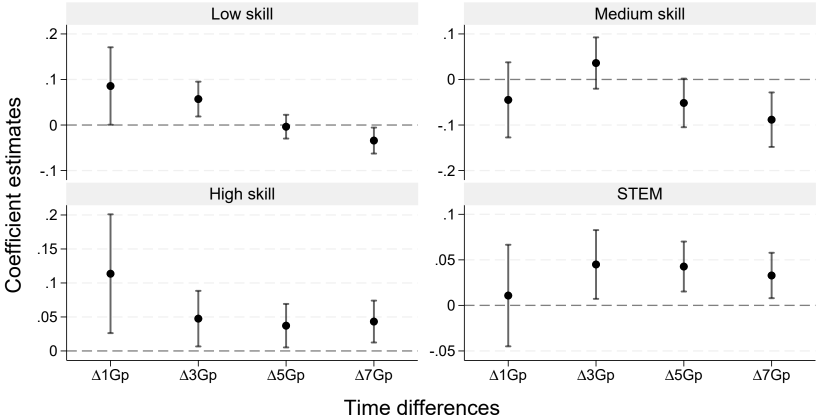
Notes: This table applies the methodology from Lee et al. [2022] to estimate valid t-ratio inference for instrumental variables. The estimates the command works on are even columns of **??**.

IV validation: monotonicity

back



Employment by skill back



KP F-Stats: 11.0; 53.4; 140.3; 160.7.
CD F-Stats: 14.9; 79.4; 174.8; 191.8.

High-skilled and STEM workers benefit the most. Low-skilled to an extent.

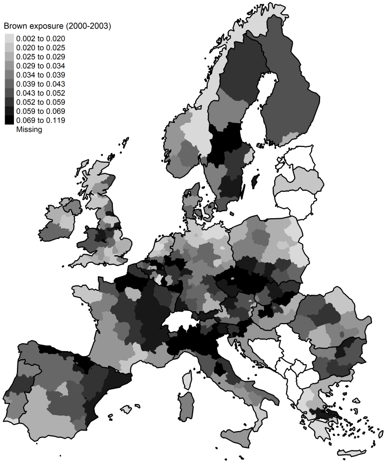
Baseline brown specialization I

- We measure brown exposure as the ratio between regional employment in polluting industries and the total regional employment

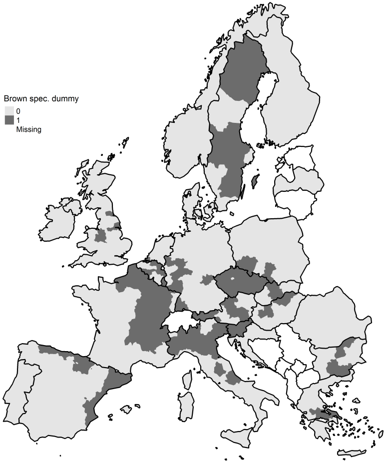
$$BP_{r,t_0} = \sum_j \frac{L_{r,j=poll,t_0}}{L_{r,t_0}}$$

- $j = poll$ contains the highest emitting manufacturing sectors (24, 25, 21, 20, 23 and 19) and the whole mining sector.
- We then measure elevated brown penetration by identifying those NUTS2 regions that have values of the just mentioned ratio above the 75th percentile.

Baseline brown specialization II



(a) Baseline level



(b) Dummy above 75th perc.

Baseline brown specialization III back

Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
	Total		*Manufacturing*		*Non-manufacturing*	
$\Delta\ GRP_{r,t3}$	0.023***	0.211***	0.007**	0.044**	0.022**	0.067
	(0.007)	(0.066)	(0.003)	(0.021)	(0.009)	(0.079)
$*\ BP\ SPEC_{r,t0}$	0.019	-0.046	0.010***	0.011	0.000	0.094
	(0.012)	(0.087)	(0.003)	(0.025)	(0.012)	(0.106)
Panel B:	*Construction*		*Services*		*Agric.+ Min.*	
$\Delta\ GRP_{r,t3}$	0.006***	0.069**	0.017**	-0.011	-0.006	0.100
	(0.002)	(0.030)	(0.008)	(0.065)	(0.008)	(0.070)
$*\ BP\ SPEC_{r,t0}$	0.004	0.015	-0.003	0.076	0.008	-0.151**
	(0.005)	(0.044)	(0.008)	(0.074)	(0.008)	(0.070)
N	3336	3336	3336	3336	3336	3336
Estimator	OLS	2SLS	OLS	2SLS	OLS	2SLS
KP F-Stat		11.1		11.1		11.1
CD F-Stat		16.6		16.6		16.6
Controls	✓	✓	✓	✓	✓	✓
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Polluting intensive regions still benefit from the expansion.