Climate Policies and the Carbon Content of Jobs

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Joint Firm Analysis Seminar organized by the National Bank of Belgium, 08/06/2023

UNIVERSITÀ DEGLI STUDI DI MILANO

FONDAZIONE ENI ENRICO MATTEI

Outline of the presentation

Climate 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.*"
- Such polarized debate **obscures** the key issues to design **fair green policy packages**:
  - In macro models **aggregated employment effects** usually **small** → Several papers **understate** the problems associated with the transition (e.g., Metcalf, 2023).
  - But **distributional effects large** for certain groups → Ensuring a smooth **reallocation** for **displaced workers** requires **identifying carbon-intensive jobs** beyond coal miners.
  - As for trade shocks, **unmanaged distributional effects** in the labour market fuel **political opposition** against climate policies (e.g., Vona, 2023).

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This paper in a nutshell

- Using very granular data on **CO2 emissions**, we build a **time-varying measure** of **carbon intensity** for **411 occupations** over the **period 2003-2019**.
- The **carbon content** of an occupation (i.e., a weighted average of the establishment/sector CO2 intensity) is used to **evaluate** the impact of two climate policies: **energy prices** (*today*) and **the EU-ETS** (*just preliminary results*).
- We empirically show that **such measure**:
  - is a better proxy of **vulnerability** than a **sector** measure and allows to compute the **share of workers** at **risk of displacement**;
  - sheds light on **heterogeneous effects** of a **climate policy**, especially on labour demand for different occupations;
  - highlights that **low-** and **middle skilled carbon-intensive** occupations are **particularly affected** by energy price shocks.

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Occupation vs. sector: evaluation of climate policies

Existing literature on environmental economics uses **sector-level measures** of exposure to estimate labour market impacts.

- The **Clean Air Act** quasi-experiment, triple-difference approach: job losses concentrated in polluting industries (Greenstone, 2002; Walker, 2011; Curtis, 2017).
- **Energy price effects**, either using shift-share instruments (Marin and Vona, 2019, 2021) or border-pair fixed effects (Kahn and Mansur, 2013): job losses significantly larger in energy-intensive sectors.
- **EU-ETS papers** combine matching and DID: no clear negative effects on employment (Marin et al., 2018; Dechezlepretre et al., 2020; Colmer et al., 2022).

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Occupational heterogeneity & climate policies

A few recent papers suggest that **policy effects** are **heterogeneous** across **skill/occupational groups** within the same sector.

- The employment impact of the **British Columbia carbon tax** negligible on aggregate (Yamazaki, 2017), but **strongly negative** on **low-skilled workers** (Yip, 2019).
- Marin and Vona (2019, 2021) show that **employment losses** induced by **energy prices** are **highly heterogeneous across occupations**, also within the same sector.
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Occupation vs. sector to measure exposure to shocks

Research in labour economics shows that occupations convey more information than sectors along several dimensions:

- **Skills** (both **general** and **specific**)
  - Kambourov and Manovskii (2008): human capital specificity resides in occupational rather than industry categories,
  - Poletaev and Robinson (2008): occupation-specific skill proximity key predictor of post-displacement earnings.
- **Exposure** to **structural shocks**
  - Skill-biased technical change literature: within-sector across occupation effects dominant,
  - Autor et al. (2003), Goos et al. (2014): routine task intensity indicator key predictor of labour market outcomes.
- **Bargaining power** and **outside option** of workers
  - Acemoglu et al. (2001): skill-biased shocks → bargaining more decentralized at the skill-level,
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Measuring occupational exposure to climate policies

However, several questions remain unanswered in these recent papers:

- Is it possible to build a **single**, **continuous** and **time-varying** occupation-based measure of **vulnerability** to climate policies similar of those of Frey and Osborne (2013) or Autor et al. (2003) for digital techs?
- To what extent **existing results** on energy prices and EU-ETS impacts **hide** substantial **heterogeneity** across occupations? Which **dimension** of **worker's heterogeneity** is the most important?
- What an **occupation-based** measure **adds** with respect to a **sector-based** one?

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Contributions

We contribute to three strands of literature:

1. **Just transition** ⇒ providing a new **measure of vulnerability** that can be implemented with **less granular** data and highlighting **new profile**s of **vulnerable workers** beyond coal miners;
2. **Labour market impacts** of **structural transformations**:
   - building a **time-varying measure** that incorporates **carbon-saving technological change**;
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Description of data

Our main analysis is at **occupation-by-establishment** level.

- **Unbalanced panel** of **establishments** for **1997-2019** from **EACEI** (Enquête Annuelle sur le Consommations d'Energie dans l'Industrie), with **unit** of analysis the **establishment** (SIRET).
  - **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 population of big manufacturing establishments (250+ employees)
- **Balanced panel** of 411 occupations from **DADS** (Déclaration Annuelle des Données Sociales), with **unit** of analysis the **establishment** (SIRET), only from 2003
  - DADS contains occupational employment shares and wages for the **universe** of French establishments → very accurate measures
  - Information on **employment** (in FTE) and **annual wages** by **occupation** (PCS)
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New metrics: carbon-content of occupations

- **Binary definition** of **brown jobs** fails to capture carbon-reducing **technological change** and **different degrees** of vulnerability **beyond coal miners**.
- We build an **index** of the **carbon content of occupations** for 400+ occupations over the period 2003-2018 capturing the **worker's outside option** to carbon pricing shocks:

$$CC_{ot} = \sum_{i=1}^{N} \frac{L_{oit}}{L_{ot}} \times \frac{CO2_{it}}{L_{it}},$$

where i indexes EACEI establishments in manufacturing and 3-digit industries for non-manufacturing sectors (JRC-Eurostat data) or manufacturing establishments not surveyed in EACEI

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Theoretical interpretation of the carbon-content

- **Carbon-task specificity**, the demand of occupations and tasks **specific** to **high-carbon productions** will decline → we expect **larger employment losses** for high-carbon occupations, less clear is **by how much**.
- **Outside option** and **wage effects**, for a worker employed in sector j, the carbon content can be approximated as:

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  - A higher carbon content reveals a **weaker bargaining position** to carbon pricing shocks.
  - But the **effect of carbon pricing** on **firm profits** and **workers' quasi-rents** is unclear (especially for the EU-ETS).
  - **Workers' selection** may increase the average workers' skills and thus wages in firms more exposed to carbon price shocks.

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Greenness indicator

- For descriptive purposes, we compare labour market dynamics of **carbon intensive** and **green occupations**.
- Carbon intensity and the greenness of an occupation capture **two different aspects** of the labour market adjustment: **vulnerability** vs. **reducing env. impact**.
- Building on our previous work (Vona *et al.*, 2015, 2018, 2019), we use a **task-based indicator** of '**greenness**':

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

- The greenness captures the **relative importance** (e.g. time spent) of **green tasks** for that occupation.
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Climate policy measures: energy prices

- As in Davis et al (2013), what we call **energy price** is, actually, the average **unit cost of energy**, i.e. expenditures divided by quantity consumed (in kWh)
- This **ratio** can be written as:

$$P_{et}^{E} = \sum_{j=1}^{J} \phi_{et}^{j} P_{et}^{j},$$

  where ϕ_{et}^{j} is the **share** of **energy** consumption of source j (i.e. gas, electr, coal, oil, etc) on **total** energy consumption, while p_{et}^{j} is the **price** of energy source j paid by **establishment** e at time t
- Similar to Jo (2022), here we distinguish between the **price of dirty** (i.e., all fossil fuels) and **clean energy** (e.g., electricity in France) → only the former should have an impact on the carbon content.

Facts about carbon-intensive occupations

1. We observe no **"unconditional" catching-up** (hard to decarbonize?), but a mild **"conditional" catching-up** in the carbon content of occupations;
2. Carbon intensive occupations are **more vulnerable in general**, being more exposed to other **skill-biased** structural shocks;
3. Carbon-intensive occupations exhibit **slower employment growth**;
4. **Wage growth** is uncorrelated (or **slightly positively correlated**) with carbon intensity;
5. Little overlapping between **greenness** and **carbon-intensity** of jobs. The two groups exhibit **opposite patterns** in terms of employment and wages.

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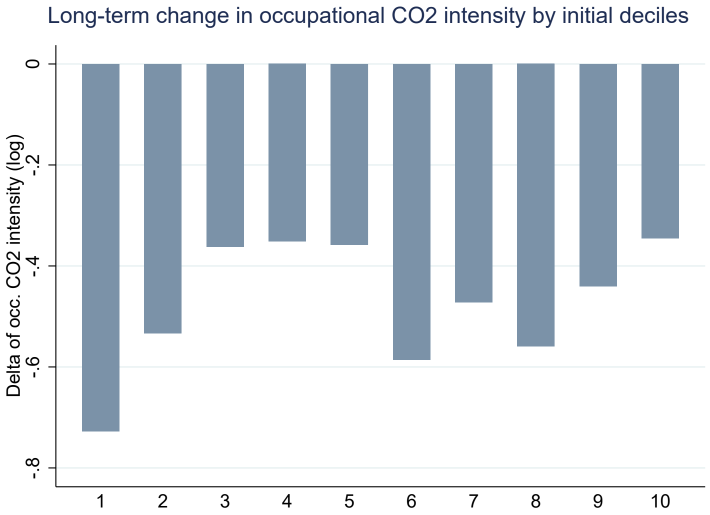

source: our elaborations on EACEI-DADS-JRC data.

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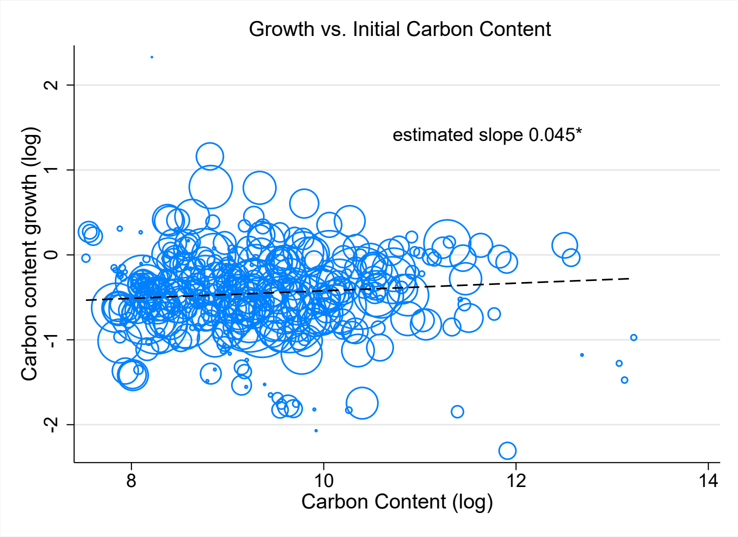

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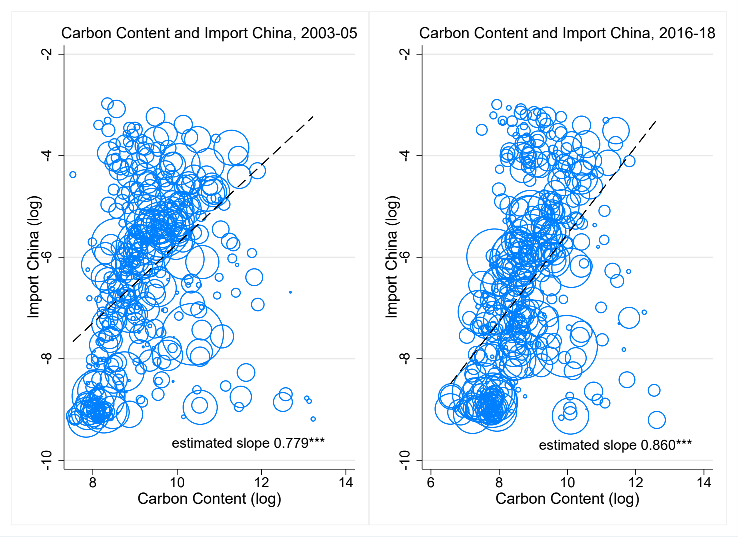
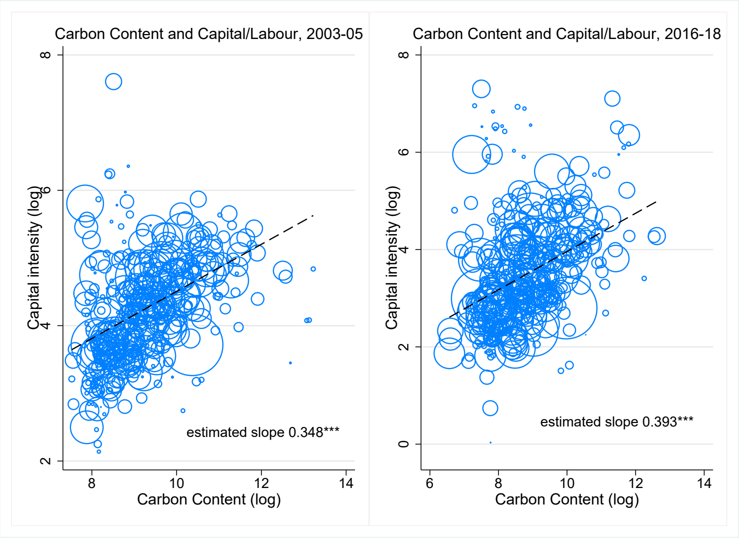
FACT II: Carbon content and trade



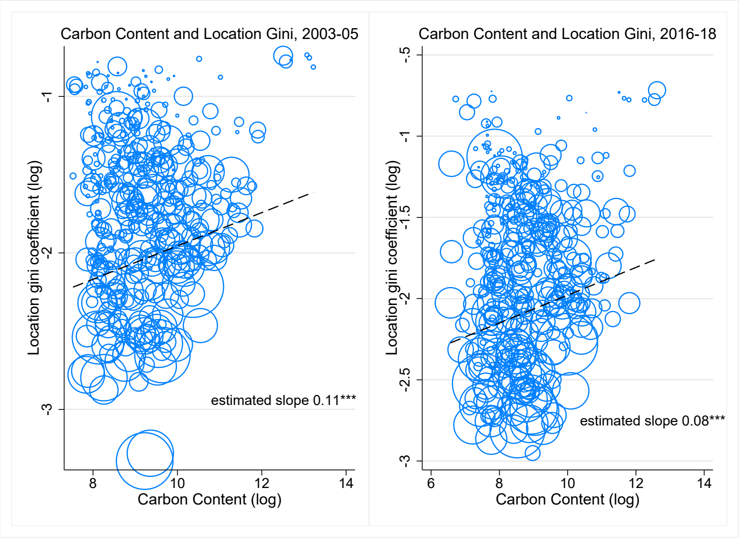
source: our elaborations on EACEI-DADS-JRC data. Slopes: β_{init} = 0.289, β_{end} = 0.418

FACT II: Carbon content and capital deepening



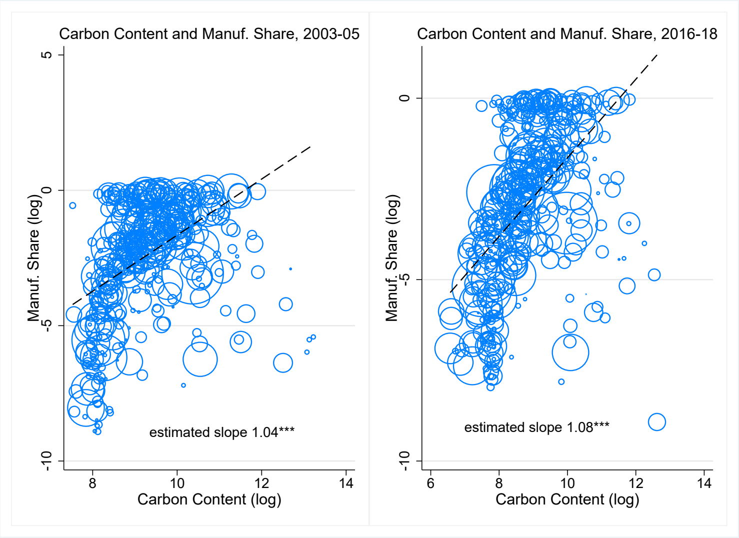
source: our elaborations on EACEI-DADS-JRC data. Slopes: $\beta_{init} = 0.313$, $\beta_{end} = 0.363$

FACT II: Carbon content and spatial concentration



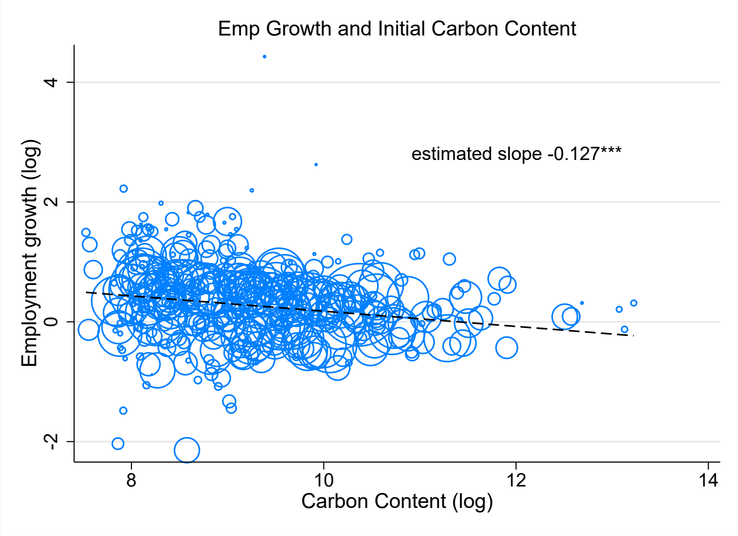
source: our elaborations on EACEI-DADS-JRC data. Slopes: $\beta_{init} = 0.107$, $\beta_{end} = 0.113$

FACT II: Carbon content and Manuf. share



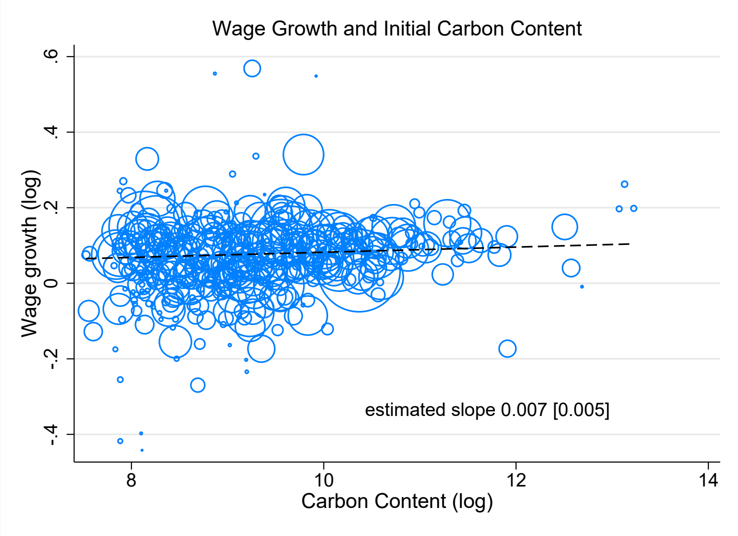
source: our elaborations on EACEI-DADS-JRC data. Slopes: $\beta_{init} = 1.144$, $\beta_{end} = 1.022$

FACT III: Initial carbon content and emp. growth



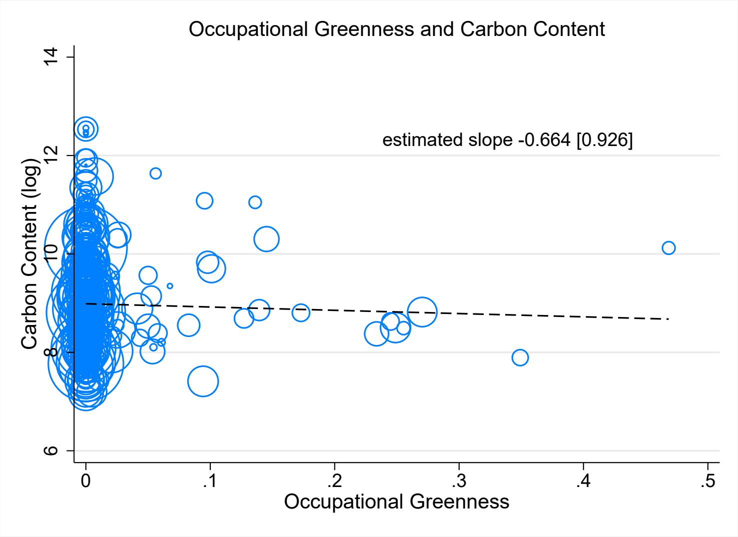
Growth-growth spec.: similar results here

FACT IV: Initial carbon content and wage growth



Growth-growth spec.: similar results here

FACT V: Green vs. carbon-intensive occupations



source: our elaborations on EACEI-DADS-JRC data

Conditional correlations

We estimate the relationship btw **wage/employment/CO2 intensity** and occupational **initial CO2 intensity** and **greenness**, controlling for: capital intensity, imports from China, etc. and occ. FE.

$$log(y_{ot}) = \beta_1 log(CC_{ot}) + \beta_2 greenness_o \times t + \gamma X'_{ot} + \mu_t(+\mu_{ot}) + \epsilon_{ot}$$

Table: Conditional correlations

Dep. var:	log(CO2/L)	log(FTE)	log(wages)
init. log(CO2/L) x time	-0.0292** (0.0119)		
log(CO2/L)		-0.083** (0.030)	0.0054 (0.0036)
Greenness x time	-0.2851 (0.2598)	0.203** (0.097)	-0.104*** (0.025)
Controls: other shocks	Yes	Yes	Yes
2-digit occ. x years F.E.	Yes	Yes	Yes
R sq	0.340	0.501	0.901
N of 4-digit occupations	411	411	411
N	2,055	2,055	2,055

Notes: FE estimates weighted by initial occ. employment FTE. Control variables: see above. Standard errors clustered by 4-digit PCS occupation in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Estimating energy price impacts

We estimate the following equation for an unbalanced panel of establishment e-occupation o pairs for the period 2003-2018:

$$log(Y_{oet}) = \beta_1 log(P^E_{et}) + \beta_2 log(CC_{ot}) + \beta_3 log(P^E_{et}) \times log(CC_{ot}) + ..$$
$$\alpha_{eo} + \xi_{st} + \phi_{rt} + \gamma_t \mathbb{1}_{k \in ETS(t)} + \eta_{ot} + X'_{ot}\mu + \varphi green_o \times t + \varepsilon_{oet}$$

where:

- Y_{oet} is FTE employment/wages (in log);
- P^E_{et} is the average price of energy in establishment e;
- CC_{ot} is the CO2 emission intensity in occupation o.
- **Favourite** specification controls for **fixed effects**: estab.-occ. (α_{eo}), sector(2-digit NACE)-by-year (ξ_{st}), region-by-year (ϕ_{rt}) and occupation-by-year (η_{ot}) as well as EU-ETS-by-year dummies ($\mathbb{1}_{k \in ETS(t)}$).
- **Main source of identifying variation**: within-estab.-occ. effects of energy price shocks net of sector-, region-, occupation- and ETS-specific trends.

Challenges for the empirical analysis

- **Zero inflation**: several establishment-by-occupation cells are zeros.
  - **Self-selection** problems affecting average occupational wages → we keep only **occupations** present in the **initial period** for **wages**.
  - For **employment**: flexible log-transformation to account for the zeros ($log(x + min/2)$) and analysis at both the 4digit occupation vs. 2digit occupation level, where less zeros.
- **Potential endogeneity** of the **occupational carbon content** → we use the **sector (3digit) CO2 intensity** to build a measure of the carbon content of the occupation.
- **Testing sector-** vs. **occupation-** effects: which one is prevalent? Recall that CC_{ot} decomposed in two components: sector of work and outside option.

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Challenges for the empirical analysis (cnt.)

- **Endogeneity** of energy prices → two 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).
- **Dirty** and **clean fuels**→ fossil fuels vs. electricity → we use **only dirty fuel prices** in the main specification controlling for **initial electricity share** of the establishment interacted with year dummies.
- For the **EU-ETS quasi-experiment**: as common practice in the literature, we combine **difference-in-difference** and **matching** to retrieve the causal effect of the EU-ETS as a function of the occupational carbon content.

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Instrumental variable

- As in Marin and Vona (2021), we build a shift-share **IV** that **only** keeps **exogenous variations** in energy **prices** and **accounts** for **both sources** of **endogeneity**

$$P^{IV}_{et} = \sum_{j=1}^{J} \phi^{j}_{e,t=presample} P^{j}_{t}$$

- **Domestic regulation** induced substantial **changes** in **prices**, especially for **electricity**;
- Prices for **other sources** respond more to **'global' prices**;
- We **shut down** endogenous **responses** of establishments to changing energy prices by weighting exogenous prices with a **time-invariant** (lagged) establishment-specific energy mix
- Energy mix observed in the **first year** available in EACEI, **lagged** at least **3 years** from the first observation.

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Endogeneity of energy prices (cnt.)

- We adapt **recent insights** on shift-share IV design to enhance the credibility of identification strategy,
- Note that the approach of treating energy price shocks **as-good-as randomly assigned** conditional on **X** applies if the number of shocks is **large** (Borusyak et al., 2021).
- Here only **four fuels** account for the bulk of energy consumed (electricity, gas, heating oil, coal) here
- 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. here
  - We account for **unobserved heterogeneity** in levels using **estab.-occ.** fixed effects.
  - We also control for **occupation and sector specific** trends correlated with LM outcomes.
  - **Exclusions restriction:** pre-sample energy mix uncorrelated with LM outcomes conditional on these controls.

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Employment, 2digit, all fuels

To ease the interpretation, the occupational carbon-intensity is net of the sample median, some stats: IQR=0.703; p(90)-p(50)=1.39. Median of the $log(energy - price) = 4.05$, $log(dirty - price) = 3.73$. The number of 2digit occ. is 29.

Table: Results for employment (2-digit occ.) - average energy price

Dep var: FTE empl (log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV	(5) FE	(6) FE-IV
Energy price (log)	-0.241***	-0.112*	-0.058***	0.0023	-0.042***	0.0035
	(0.0099)	(0.0584)	(0.0068)	(0.0573)	(0.0069)	(0.0559)
Carbon content of occ. (log)	1.583***	1.598***	-0.045***	-0.027***		
	(0.0070)	(0.0072)	(0.0075)	(0.0081)		
Energy price x Carbon cont. of occupations	-0.492***	-0.446***	-0.084***	-0.180***	-0.045***	-0.189***
	(0.0145)	(0.0235)	(0.0063)	(0.0117)	(0.0068)	(0.0369)
Reg.-year FE	✓	✓	✓	✓	✓	✓
Sect.-year FE	✓	✓	✓	✓	✓	✓
Estab. FE	✓	✓				
Occ.-estab. FE			✓	✓	✓	✓
Occ.(2-digit)-year FE					✓	✓
F test of excluded IV		277.2		276.8		259.5
N of establishments	13327	13327	13120	13120	13120	13120
N. obs	1206166	1206166	1204053	1204053	1204053	1204053

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control: ETS-year dummies.

Employment, 2digit, dirty price

Table: Results for employment (2-digit occ.) - average price of fossil fuels

Dep var: FTE empl (log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV	(5) FE	(6) FE-IV
Dirty-energy price (log)	-0.173***	-0.315***	-0.038***	-0.069	-0.022***	-0.090
	(0.0082)	(0.0648)	(0.0051)	(0.0620)	(0.0051)	(0.0581)
Carbon content of occ. (log)	1.632***	1.665***	-0.040***	-0.021**		
	(0.0073)	(0.0076)	(0.0079)	(0.0087)		
Dirty price x Carbon cont. of occupations	-0.335***	-0.482***	-0.052***	-0.137***	-0.019***	-0.181***
	(0.0140)	(0.0266)	(0.00489)	(0.0102)	(0.00506)	(0.0458)
Decile electr. share-year FE	✓	✓	✓	✓	✓	✓
Reg.-year FE	✓	✓	✓	✓	✓	✓
Sect.-year FE	✓	✓	✓	✓	✓	✓
Estab. FE	✓	✓				
Occ.-estab. FE			✓	✓	✓	✓
Occ.(2-digit)-year FE					✓	✓
F test of excluded IV		134.0		134.1		138.6
N of establishments	10398	10398	10398	10398	10398	10398
N. obs	1004495	1004495	1004495	1004495	1004495	1004495

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional control: ETS-year dummies.

Employment, 2digit, dirty, multiple exposure

Table: Results for employment (2-digit occupations) - overlapping exposures

Dep var: FTE empl (log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV
Dirty-energy price (log)	-0.0169***	-0.0976	-0.0159***	-0.0595
	(0.0061)	(0.0952)	(0.0058)	(0.0714)
Dirty-energy price x Occ. Carbon content (log)	-0.0186***	-0.182***	-0.0147**	-0.152***
	(0.0051)	(0.0449)	(0.0064)	(0.0491)
Dirty-energy price x Sect. Carbon content (log)	-0.00451	0.00481		
	(0.0029)	(0.0400)		
Dirty-energy price x Occ. Gini location coeff.			-0.0083	-0.774
			(0.0671)	(0.543)
Dirty-energy price x Occ. import penetration			0.0574*	0.407
			(0.0328)	(0.352)
Dirty-energy price x Occ. capital intensity (log)			-0.0285***	-0.110**
			(0.0095)	(0.0448)
F test of excluded IV		36.67		57.58
N of establishments	10398	10398	10398	10398
N. obs	1004495	1004495	1004495	1004495

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies.

Employment, 4digit, main results

Table: Results for employment (4-digit occupations)

Dep var: FTE empl (log)	(1)	(2)	(3)
Energy price (log)	0.0613		
	(0.0386)		
Energy price (log) x Carbon cont. of occupation (log)	-0.0874***		
	(0.0145)		
Dirty-energy price (log)		-0.0242	-0.0947
		(0.0385)	(0.0713)
Dirty-energy price (log) x Carbon cont. of occupations (log)		-0.0414**	-0.0460***
		(0.0172)	(0.0166)
Dirty-energy price (log) x Sectoral emission intensity (log)			0.0427
			(0.0275)
F test of excluded IV	202.1	114.2	28.58
N of establishments	13048	10345	10345
N. obs	5429943	4701391	4701391

Notes: Unit of analysis: establishment-occupation (4-digit PCS) pair. IV-FE model. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies (except column 1).

Employment, 4digit, by occ.

Table: Results for employment (4-digit occupations) - by occupational skill level

Dep var: FTE empl (log)	Low-skill occ	Medium-skill occ	High-skill occ
Dirty-energy price (log)	-0.0536	-0.0272	-0.00106
	(0.0644)	(0.0442)	(0.0599)
Dirty-energy price (log) x	-0.100***	-0.0464**	0.0327
Carbon cont. of occupations (log)	(0.0354)	(0.0193)	(0.0329)
F test of excluded IV	102.3	117.4	102.0
N of establishments	10028	10343	10190
N. obs	689591	2871974	1139826

Notes: Unit of analysis: establishment-occupation (4-digit PCS) pair. IV-FE model. Standard errors clusterd by establishment in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies.

Wage, 2digit, all fuels

Table: Results for wages (2-digit occupations) - average energy price (all energy inputs)

Dep var: hourly wage(log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV	(5) FE	(6) FE-IV
Energy price (log)	-0.022***	-0.0326	0.0032	-0.037**	-0.0025	-0.052***
	(0.0031)	(0.0257)	(0.0023)	(0.0183)	(0.0023)	(0.0172)
Carbon content occ. (log)	-0.069***	-0.071***	0.072***	0.067***		
	(0.0023)	(0.0024)	(0.0037)	(0.0039)		
Energy price x Carb. cont. of occupation (log)	-0.073***	-0.054***	0.014***	0.042***	-0.010***	-0.0198
	(0.005)	(0.0081)	(0.0029)	(0.0056)	(0.0036)	(0.0177)
Reg.-year FE	✓	✓	✓	✓	✓	✓
Sect.-year FE	✓	✓	✓	✓	✓	✓
Estab. FE	✓	✓				
Occ.-estab. FE			✓	✓	✓	✓
Occ.(2-digit)-year FE					✓	✓
F test of excluded IV		289.4		288.8		267.0
N of establishments	13116	13116	13116	13116	13116	13116
N. obs	849954	849954	849954	849954	849954	849954

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: sector-year dummies, region-year dummies, ETS-year dummies.

Wage, 2digit, dirty

Table: Results for wages (2-digit occupations) - average price of fossil fuels

Dep var: hourly wage (log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV	(5) FE	(6) FE-IV
Dirty-energy price (log)	-0.016***	-0.059**	0.004***	-0.021	0.0004	-0.033**
	(0.0024)	(0.0277)	(0.0016)	(0.0185)	(0.0016)	(0.0153)
Carbon content occ. (log)	-0.064***	-0.064***	0.072***	0.067***		
	(0.0024)	(0.0026)	(0.0039)	(0.0042)		
Dirty price x Carb. cont.	-0.054***	-0.067***	0.0095***	0.033***	-0.0045	0.0156
of occupation (log)	(0.0047)	(0.0094)	(0.0024)	(0.005)	(0.0028)	(0.0243)
Reg.-year FE	✓	✓	✓	✓	✓	✓
Sect.-year FE	✓	✓	✓	✓	✓	✓
Estab. FE	✓	✓				
Occ.-estab. FE			✓	✓	✓	✓
Occ.(2-digit)-year FE					✓	✓
F test of excluded IV		151.2		156.2		161.9
N of establishments	10854	10854	10854	10854	10854	10854
N. obs	732991	732991	732991	732991	732991	732991

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies.

Wage, 2digit, dirty, multiple exp.

Table: Results for wages (2-digit occupations) - overlapping exposures

Dep var: hourly wage (log)	(1) FE	(2) FE-IV	(3) FE	(4) FE-IV
Dirty-energy price (log)	-0.0009	-0.047*	0.000	-0.043***
	(0.0016)	(0.0246)	(0.0016)	(0.0159)
Dirty price x Carbon content	-0.005*	0.008	-0.0015	0.0266
of occupation (log)	(0.0028)	(0.0109)	(0.0039)	(0.0278)
Dirty-energy price (log) x Sect.	0.0012	0.0143		
emission intensity (log)	(0.0011)	(0.0239)		
Dirty price x Occ.			-0.0078	-0.230
Gini location coefficient			(0.0303)	(0.236)
Dirty price x Occ.			-0.0091	-0.0644
import penetration			(0.0103)	(0.0889)
Dirty price x Occ.			-0.0053	-0.0160
capital intensity (log)			(0.0042)	(0.0170)
F test of excluded IV		42.29		66.36
N of establishments	10854	10854	10854	10854
N. obs	732991	732991	732991	732991

Notes: Unit of analysis: establishment-occupation (2-digit PCS) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies.

Wages, 4digit, main results

Table: Results for wages (4-digit occupations)

Dep var: hourly wage (log)	(1)	(2)	(3)
Energy price (log)	-0.0260		
	(0.0184)		
Energy price (log) x Carbon cont. of occupation (log)	-0.0221***		
	(0.00722)		
Dirty-energy price (log)		-0.0127	-0.00311
		(0.0161)	(0.0239)
Dirty-energy price (log) x Carbon cont. of occupations (log)		-0.0198**	-0.0183**
		(0.00819)	(0.00777)
Dirty-energy price (log) x Sectoral emission intensity (log)			-0.00630
			(0.00959)
F test of excluded IV	200.1	136.1	39.64
N of establishments	13036	10338	10338
N. obs	2335130	2030497	2030497

Notes: Unit of analysis: establishment-occupation (4-digit PCS) pair. IV-FE model. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies (except column 1).

Wage, 4digit, by occupation

Table: Results for wages (4-digit occupations) - by occupational skill level

Dep var: average hourly wage (log)	Low-skill occ	Medium-skill occ	High-skill occ
Dirty-energy price (log)	-0.00437	-0.0160	-0.00235
	(0.0385)	(0.0170)	(0.0282)
Dirty-energy price (log) x	-0.0195	-0.0265***	0.00801
Carbon cont. of occupations (log)	(0.0287)	(0.00878)	(0.0204)
F test of excluded IV	139.4	139.7	97.96
N of establishments	9402	10321	9858
N. obs	196002	1286159	548336

Notes: Unit of analysis: establishment-occupation (4-digit PCS) pair. IV-FE model. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Additional controls in all specification: occupation-establishment fixed effects, occupation-year dummies, sector-year dummies, region-year dummies, ETS-year dummies, initial decile of electricity share x year dummies.

Discrete policy change: the EU-ETS

- We also consider the introduction of the **EU-ETS** as a **discrete policy change** affecting the **price** of **fossil fuels** for treated establishments
- We follow the **standard approach** popularized by Calel and Dechezlepretre (2016) of **matching** treated establishment with non-treated ones with **similar** characteristics
  - **Matching variables** (measured in **2004**, **EACEI sample** of that year):
    - Energy-related **CO2 emissions** (log)
    - Establishment **size** (dummy for 250+ employees FTE)
    - Shares of **employment** in **HS** and **MS** occupations
    - Average **carbon content of occupations** of employees in the establishment (log)
    - **Sector** dummies (2-digit) ⇒**Exact match** on **sector**
  - **One nearest neighbour** with **replacement** and **caliper** (1/4 SD of propensity score), common **support** ⇒ **279 treated**, **158 matched** controls
- We estimate a **diff-in-diff** on the **matched sample**, **interacting** the treatment with the **carbon content** of occupations

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Balancing (I)

Table: Balancing between treated and untreated establishments: matching variables

Matching variables (year 2004)	Treated	Untreated	t-test	Treated match	Untreated match	t-test
CO2 emissions (log)	4.95	0.92	38.17***	4.70	4.75	-0.36
Medium-big estab (>250 emp)	0.52	0.24	11.69***	0.48	0.52	-0.85
Share of high skill	0.112	0.123	-1.66*	0.113	0.118	-0.50
Share of middle skill	0.77	0.677	8.60***	0.760	0.770	-0.79
Average carbon cont. of occ. (log)	10.12	10.04	11.01***	10.12	10.12	-0.60

Balancing (II)

Table: Balancing between treated and untreated establishments: other variables

Matching variables (year 2004)	Treated	Untreated	t-test	Treated match	Untreated match	t-test
Energy use (log)	7.14	3.19	39.52***	6.93	6.76	1.34
Employment FTE (log)	5.46	4.58	15.11***	5.34	5.46	-1.32
Electricity share	0.287	0.584	-19.93***	0.292	0.249	2.61**
Average wage (log)	10.16	9.98	13.93***	10.15	10.12	2.05**
Capital intensity of occ. (log)	4.52	4.49	8.84***	4.52	4.52	-0.15

EU-ETS: employment, 2digit

Table: Effect of the EU-ETS - employment

Dep var: FTE empl (log)	(1)	(2)	(3)	(4)
ETS x Post (2005-2019)	-0.0152		0.0216	
	(0.0405)		(0.0401)	
Carbon content of occ. (log)	0.0434	0.0559		
	(0.0330)	(0.0341)		
ETS x Post (2005-2019) x	-0.0777***		-0.0245	
Carbon content of occ. (log)	(0.0200)		(0.0263)	
ETS x Phase 1 (2005-2007)		0.0110		-0.00247
		(0.0300)		(0.0299)
ETS x Phase 2 (2008-2012)		-0.0376		-0.00148
		(0.0541)		(0.0576)
ETS x Phase 3 (2013-2019)		0.00614		0.0959
		(0.0663)		(0.0766)
ETS x Phase 1 (2005-2007) x		-0.00399		-0.0338
Carbon content of occ. (log)		(0.0163)		(0.0277)
ETS x Phase 2 (2008-2012) x		-0.0854***		-0.0379
Carbon content of occ. (log)		(0.0206)		(0.0312)
ETS x Phase 3 (2013-2019) x		-0.0838***		0.0320
Carbon content of occ. (log)		(0.0246)		(0.0368)
Occ. (2-digit)-year FE			✓	✓
N. obs	99784	99784	99784	99784

Notes: Unit of analysis: establishment-occupation (2-digit) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Fixed effect model on matched sample. Additional controls: sector-by-year dummies, region-by-year dummies. Matching based on propensity score.

EU-ETS: wage, 2digit

Table: Effect of the EU-ETS - wage

Dep var: average hourly wage (log)	(1)	(2)	(3)	(4)
ETS x Post (2005-2019)	-0.0155*		-0.0177**	
	(0.00907)			
Carbon content of occ. (log)	0.0798***	0.0810***		
	(0.0140)	(0.0147)		
ETS x Post (2005-2019) x Carbon content of occ. (log)	0.0173**		0.0160	
	(0.00804)		(0.0118)	
ETS x Phase 1 (2005-2007)		-0.0138		-0.0148*
		(0.00891)		(0.00834)
ETS x Phase 2 (2008-2012)		-0.0130		-0.0184*
		(0.0107)		(0.0101)
ETS x Phase 3 (2013-2019)		-0.0215*		-0.0241*
		(0.0125)		(0.0126)
ETS x Phase 1 (2005-2007) x Carbon content of occ. (log)		0.00219		0.00467
		(0.00790)		(0.0104)
ETS x Phase 2 (2008-2012) x Carbon content of occ. (log)		0.00322***		0.0246*
		(0.00921)		(0.0134)
ETS x Phase 3 (2013-2019) x Carbon content of occ. (log)		0.00621		0.00361
		(0.00912)		(0.0133)
Occ. (2-digit)-year FE			✓	✓
N. obs	68578	68578	68578	68578

Notes: Unit of analysis: establishment-occupation (2-digit) pair. Standard errors clusterd by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Fixed effect model on matched sample. Additional controls: sector-by-year dummies, region-by-year dummies. Matching based on propensity score.

Preliminary quantification of energy prices on employment

How to interpret our results? How many workers are at risk of displacement for carbon pricing?

- We do **not** use **weights** as the **EACEI sample** is **highly selected** (see Marin and Vona, 2021).
- The **estimated effect** is a **cross-elasticity of labour demand**, but it is a **"LATE"** and does not account for **compositional effects.**
- Marin and Vona (2021) and Dussaux (2019) show that **compositional effects** can **both mitigate** and **amplify** employment effects:
    - Exit of carbon-intensive firms amplifies it;
    - Labour reallocation towards less-carbon intensive, more productive establishments (both within the firm and the industry) mitigates it;
- Explicitly computing **long-term effects**, Marin and Vona (2021) show that the effect estimated here is 40% **smaller.**

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Preliminary quantification (cnt.)

- Given these premises, our estimates may **slightly understate** the **risk of displacement**.
- We compute the **share of workers** at **risk of displacement** in **high-carbon occupations** as follows:

$$RiskDisplCC_t = \sum_{o=1}^{411} \frac{L_{ot}}{L_t} \times \frac{L_{o \in manuf,t}}{L_{ot}} \times (\mathbb{1}_{o \in \Theta(\hat{\beta}_o)} - \mathbb{1}_{o \in green}),$$

  - $\frac{L_{ot}}{L_t} \times \frac{L_{o \in manuf,t}}{L_{ot}}$ captures the size of the occupations X the exposure to the treatment, i.e. working in manufacturing;
  - $(\mathbb{1}_{o \in \Theta} - \mathbb{1}_{o \in green})$ is the subset of occupations for which estimated energy price effects ($\hat{\beta}_o$) are negative and stat. significant and not green.
- Approximating the set $\Theta(\hat{\beta}_o)$ to contain the **last quartile** of **high-carbon occupations**, we obtain: $RiskDisplCC_{2003-06} = 8.4\%$ and $RiskDisplCC_{2015-18} = 5.7\%$

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Mechanisms behind the wage effects

- **Induced compositional effects**, which are induced by carbon price shocks, vs. **loss of rents**, which are usually higher in carbon-intensive sectors:
  - **AKM model**: estimate estab.-, worker- and estab.-by-worker fixed effects for the **universe of French companies** and **specific sub-periods** (Babet et al., 2022).
  - **Re-estimate** the effect of the **carbon pricing shocks** on those FE aggregated at the occupation-by-establishment level.
- **Stayers** vs. **movers**: we know that, especially in rigid labour markets such as the French one, wage effects more likely to emerge for movers.
  - Replicate the analysis for **various types** of **movers**: across occupations, across sectors and across occupation-sectors.

THANKS FOR YOUR ATTENTION

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Labour in the Low-Carbon Transition, new program at the FEEM: https://www.feem.it/en/ricerca/programmi/labour-in-the-low-carbon-transition/

Top Occupations in terms of carbon content

Table: Top occupations in terms of CO2 emission intensity back

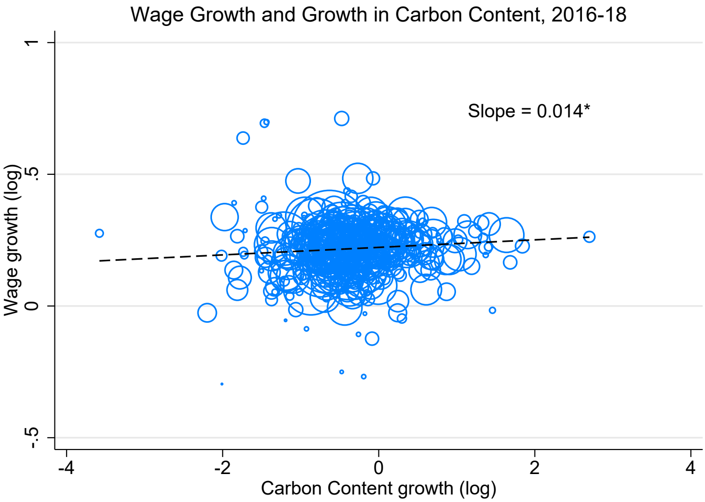
Job title	CO2/L init. (log)	*Delta* CO2/L (log)	Manuf Emp Sh
Capitaines timoniers navigation fluviale	13.20	-0.95	0.01
Officiers, cadres techniques marine marchande	13.13	-1.47	0.00
Matelots marine marchande	13.07	-1.28	0.01
Maîtres d'équipage marine marchande, pêche	12.69	-1.18	0.02
Officiers, cadres navigants techniques aviation civile	12.57	-0.03	0.01
Hôtesses de l'air, stewards	12.51	0.11	0.00
Techniciens production, distribution ind. (énergie/eau/chauffage)	12.01	-0.16	0.07
Agents non-qualifiés services exploitation transports	11.91	-2.20	0.02
Mineurs qualifiés, autres ouvriers qualifiés extraction	11.80	-0.39	0.10
Pilotes d'installation lourde industries transformation	11.78	0.21	0.96
Bobiniers qualifiés	11.69	-3.58	0.92
Responsables commerciaux, administratifs transports voyageurs	11.63	0.12	0.00
Techniciens production, contrôle-qualité industries transformation	11.56	-0.73	0.90
Agents de maîtrise en fabrication	11.56	-0.46	0.93
Ouvriers qualifiés, autres ind. (énergie/eau/chauffage)	11.55	-0.19	0.14
Ingénieurs, cadres production distribution énergie/eau	11.55	0.07	0.07
Ouvriers production non-qualifiés imprimerie/presse/édition	11.54	-0.82	0.63
Conducteurs d'engin lourd de manœuvre	11.53	-0.41	0.13
Agents services commerciaux transports voyageurs	11.51	-0.74	0.00
Conducteurs d'engin lourd de levage	11.48	-0.41	0.32
Unweighted averages occupation (top 20)	12.01	-0.72	0.26
Unweighted averages occupation (all)	9.29	-0.35	0.23

Top Occupations in terms of carbon content

Table: Top occupations in terms of CO_2 emission intensity (cnt.)

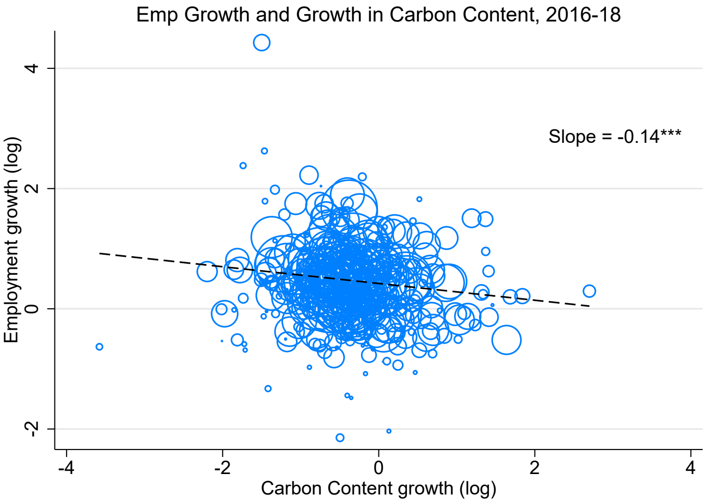
Job title	Imp China (log)	K/L (log)	Spat. Gini	Wage (log)
Capitaines timoniers navigation fluviale	-8.7	4.4	0.44	10.4
Officiers, cadres techniques marine marchande	-9.1	5.5	0.47	10.9
Matelots marine marchande	-7.4	5.4	0.47	10.2
Maîtres d'équipage marine marchande, pêche	-7.7	5.1	0.47	10.3
Officiers, cadres navigants techniques aviation civile	-9.6	4.6	0.46	11.6
Hôtesses de l'air, stewards	-11.6	4.5	0.48	10.3
Techniciens production, distribution ind. (énergie/eau/chauffage)	-7.0	6.1	0.15	10.2
Agents non-qualifiés services exploitation transports	-7.7	5.3	0.21	9.9
Mineurs qualifiés, autres ouvriers qualifiés extraction	-6.0	5.0	0.17	10.0
Pilotes d'installation lourde industries transformation	-4.2	4.8	0.30	10.2
Bobiniers qualifiés	-3.2	3.5	0.34	10.0
Responsables commerciaux, administratifs transports voyageurs	-9.4	5.4	0.23	10.3
Techniciens production, contrôle-qualité industries transformation	-4.2	4.9	0.17	10.2
Agents de maîtrise en fabrication	-3.8	4.5	0.18	10.3
Ouvriers qualifiés, autres ind. (énergie/eau/chauffage)	-6.1	7.4	0.13	10.1
Ingénieurs, cadres production distribution énergie/eau	-6.8	6.8	0.19	10.9
Ouvriers production non-qualifiés imprimerie/presse/édition	-4.8	3.6	0.24	9.7
Conducteurs d'engin lourd de manœuvre	-6.3	4.6	0.20	10.1
Agents services commerciaux transports voyageurs	-10.1	4.8	0.17	10.0
Conducteurs d'engin lourd de levage	-5.3	4.2	0.18	10.1
Unweighted averages occupation (top 20)	-6.96	5.02	0.28	10.28
Unweighted averages occupation (all)	-7.01	4.05	0.20	10.18

FACT IV: Growth-growth carbon content and wages



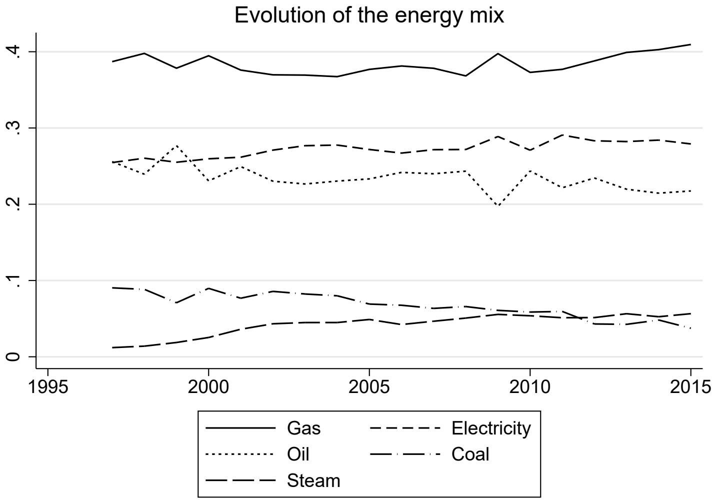
source: our elaborations on EACEI-DADS-JRC data Back

FACT III: Growth-growth carbon content and emp.



source: our elaborations on EACEI-DADS-JRC data Back

Energy mix



source: our elaborations on EACEI data

Back

Testing for parallel trends (from Marin and Vona, 2021)

Table: Tests for different trends for establishments with different initial energy mixes (unbalanced panel)

Dependent variable: Full-time equivalent employment (in log)				
F test: joint significance of electr share x time dummies	4.227	4.125	2.381	1.411
p-value	0.002	0.002	0.0493	**0.208**
F test: joint significance of gas share x time dummies	1.657	1.981	1.354	1.490
p-value	0.157	0.0946	**0.247**	**0.202**
Dependent variable: Average wage per emplyee FTE (euro, in log)				
F test: joint significance of electr share x time dummies	1.339	0.383	0.374	0.399
p-value	**0.253**	**0.821**	**0.827**	**0.810**
F test: joint significance of gas share x time dummies	1.583	1.236	1.090	1.151
p-value	**0.176**	**0.293**	**0.359**	**0.331**
Year dummies	Yes	-	-	-
Region x year dummies	-	Yes	Yes	Yes
Sector (2-digit) x year dummies	-	-	Yes	Yes
Additional controls	-	-	-	Yes

Notes: Fixed effect model. Standard errors clustered by establishment in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Sample: establishments of the 1997 sample in years 2001 (included establishments should be observed at least twice). Regressions include the interaction between initial shares (of gas and electricity, respectively) and year dummies. Gas includes natural gas, butane-propane, other gases. N=32676 (28783 for CO_2).

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