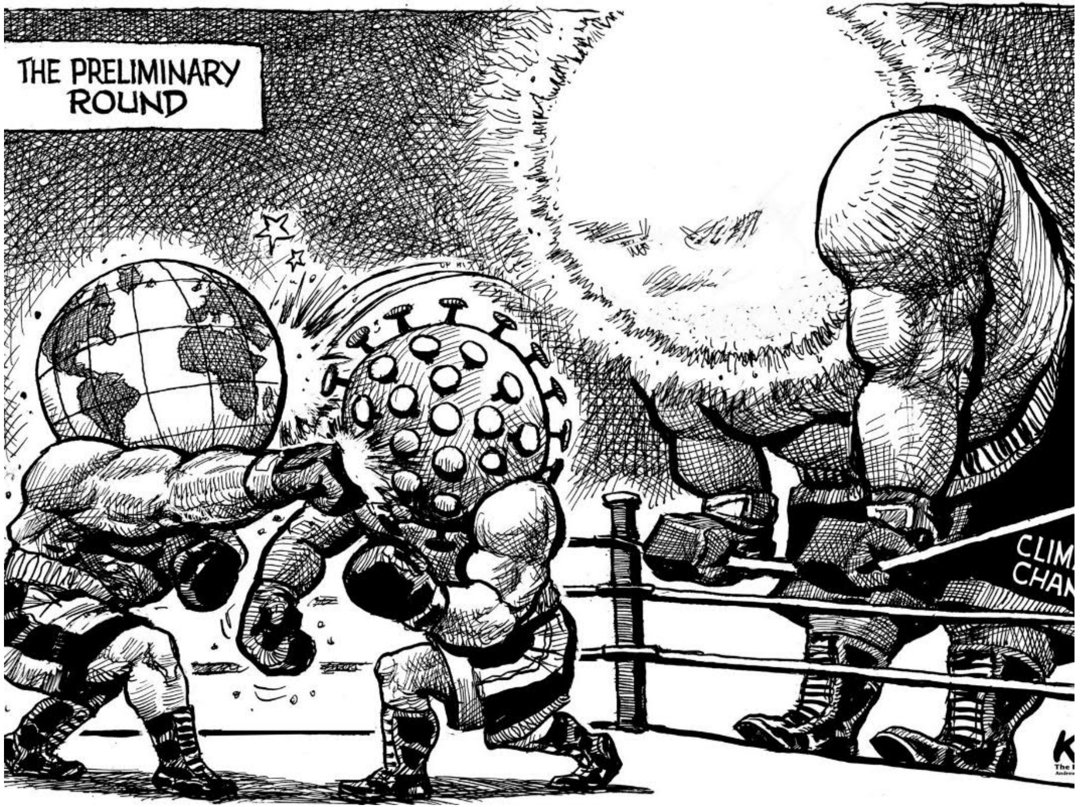
The impact of transition policies on innovation and TFP growth in the EA

Testing the Porter Hypothesis



NBB, 18/04/2024

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Motivation

- New EU Climate Laws → more ambitious objective of net zero GHG emissions by 2050
- Adoption of increasingly stringent environmental policies: 1) market (carbon pricing); 2) non-market (standards); and 3) technology support (subsidies)
- Silver lining of green transition: **the Porter Hypothesis** (Porter and van der Linde 1995): environmental policy might spur (green) innovation over the long-term and enhance profitability and productivity growth which might compensate possible short-term losses
  - Strong PH: more stringent environmental regulation increases productivity growth (benefits > costs)
  - Weak PH: more stringent environmental regulation increases innovation
  - Narrow PH: market-based regulation are less harmful than non-market measures for productivity
- Empirical evidence is yet inconclusive and faced with caveats: single reforms, country level analysis, (lack of) identification of causal impact, possible endogeneity

Research questions and contributions

Research questions:

- What are the effects of more stringent environmental policies on productivity (LP and TFP) growth and innovation at country and firm level?
- What type of policies are most effective?
- Are all firms affected in the same way by environmental policies?

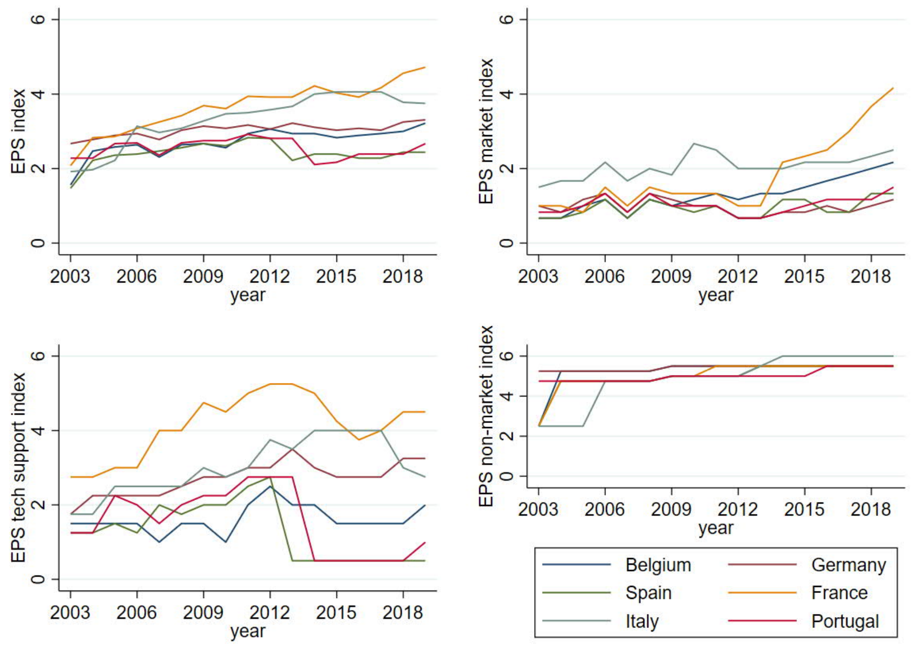
Key contributions

- Use of firm-level data for 6 EA countries between 2003-2019 to measure firm's performance
- Estimation of firm-level CO2 equivalent emissions to identify each firm's exposure to regulation
- Analysis of dynamic impacts over a 5-year horizon with local projections
- Comparison of impacts of different types of policy and impacts on different firms

Data

OECD Environmental Policy Stringency (EPS) indicator

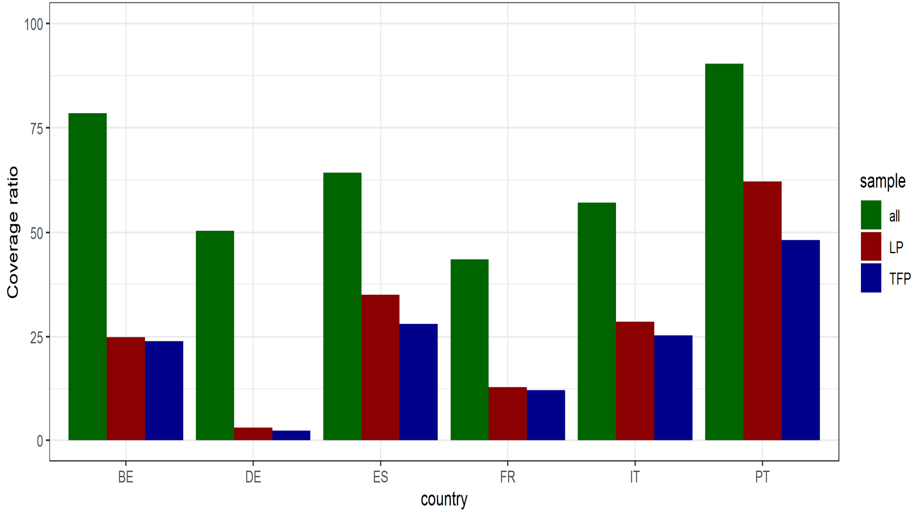
- 24 OECD countries, 1990–2020 (Kruse et al., 2022)
- 3 sub-indicators: market, non-market, technnology support
- Range: 0 to 6 (very stringent)
- Focus on positive changes (more stringent regulation) and top 25% changes → stationary, not serially correlated



Orbis & iBACH: balance sheets

- Large firm-level dataset: Belgium, France, Germany, Italy, Portugal and Spain; 2003-2019
- Sample preparation following Kalemli-Ozcan et al. (2015) +
  - Firms with at least 1 employee and at least 2 consecutive observations
  - Nonfinancial and non-governmental sectors, without real estate and mining
  - Final sample includes 2.5 million firms (18 million observations)
- Total Factor Productivity: estimated a la Ackerberg et al. (2015)
- Labour productivity: real value added divided by number of employees

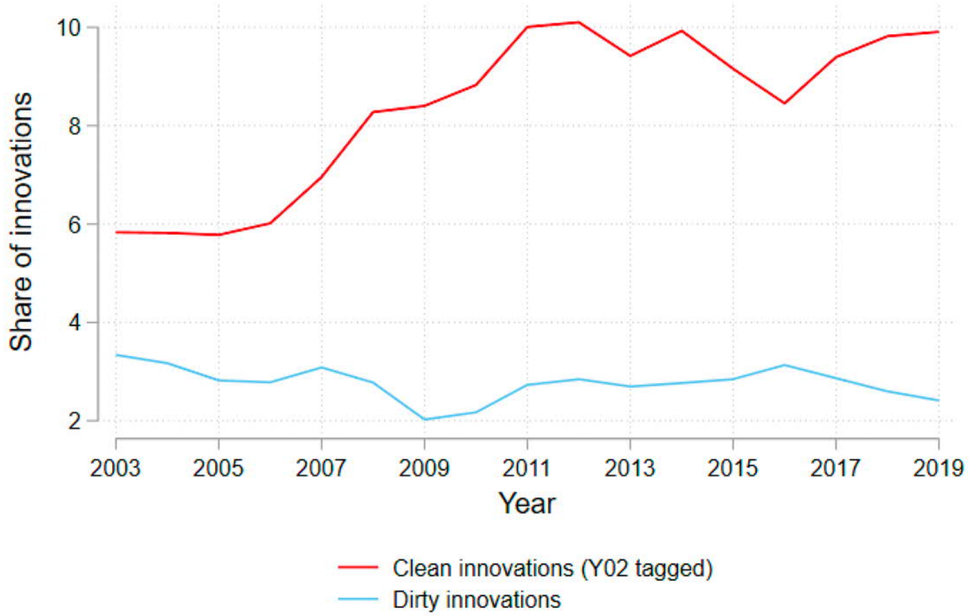
Coverage ratio



Patent data

- Data from **Orbis IP database**; aggregated to patent family level to avoid double-counting
- Cooperative Patent Classification (CPC) allows for a detailed technological disaggregation of innovation:
  - **Clean innovations:** climate change mitigation technologies
  - **Dirty innovations:** definition follows Dechezleprêtre et al. (2014) and includes e.g. fossil fuel energy generation or internal combustion engines
- Approx. 100,000 firm-year observations matched (only a minority of firms patent)

Share of clean and dirty innovations



CO_2 equivalent emissions of firms

- Urgentem data on CO_2 equivalent emissions (35k large firms), merged with ORBIS to get balance sheets of those firms
- Machine learning algorithm: Extreme Gradient Boosting (XGBoost)
  - Selects the regressors and finds the best non-linear patterns to estimate the dependent variable (CO_2)
- Estimation of CO_2 equivalent emission bins (0 low pollution – 9 high pollution)

Confusion matrix: actual vs estimated emission bins (test sample)

	Re12									
A	0	1	2	3	4	5	6	7	8	9
0	168	88	30	31	18	8	5	7	6	3
1	56	117	54	22	21	13	10	3		2
2	29	68	87	44	28	42	17	7	11	
3	11	28	57	65	62	49	28	7	10	1
4	13	14	51	55	72	53	28	27	26	9
5	6	21	21	45	47	72	35	29	22	9
6	8	10	15	20	39	57	61	64	21	5
7	4	2	5	9	25	32	72	96	69	29
8	2	6	4	6	7	13	38	39	99	42
9	3	1	1	2	4	6	4	27	58	202

Empirical Strategy

Empirical strategy

i) Aggregate (country-level) analysis

ii) Granular (firm-level) analysis incl. heterogeneity analysis

Local projections (Jordà, 2005)

1) Capturing dynamic effects
2) Less prone to miss-specification (than VARs)
3) Flexibility (to deal with endogeneity) → fixed effects, interaction effects

Identification according to Rajan and Zingales (1998):

high exposed firms (highly polluting) are more affected by regulatory changes (more stringent policies)

Local projection specification

$$\ln(y_{f,t+h}) - \ln(y_{f,t-1}) = \beta_1^h EPS_{f,t} + \beta_2^h CO2_{i,t-1} + \boxed{\beta_3^h (EPS_{i,t} * CO2_{f,t-1})} + \gamma_1^h X_{i,t} + \gamma_2^h Z_{f,t} + $$
$$+ FE_i + FE_t + FE_s + FE_f + \epsilon_{f,t+h} \qquad h = 0, \dots, 5$$

y … productivity (TFP, Labour productivity) of firm f in country i, and year t

EPS … positive change (more stringent) in EPS index (sub-indicator)
or = 1 if change in top 25% of change distribution

CO2 … = 1 if firm among top 6 emission bins (according to XGBoost)

X … country controls: cyclical position of the country, R&D expenditure, level of economic development labour and product market regulations (before reform)

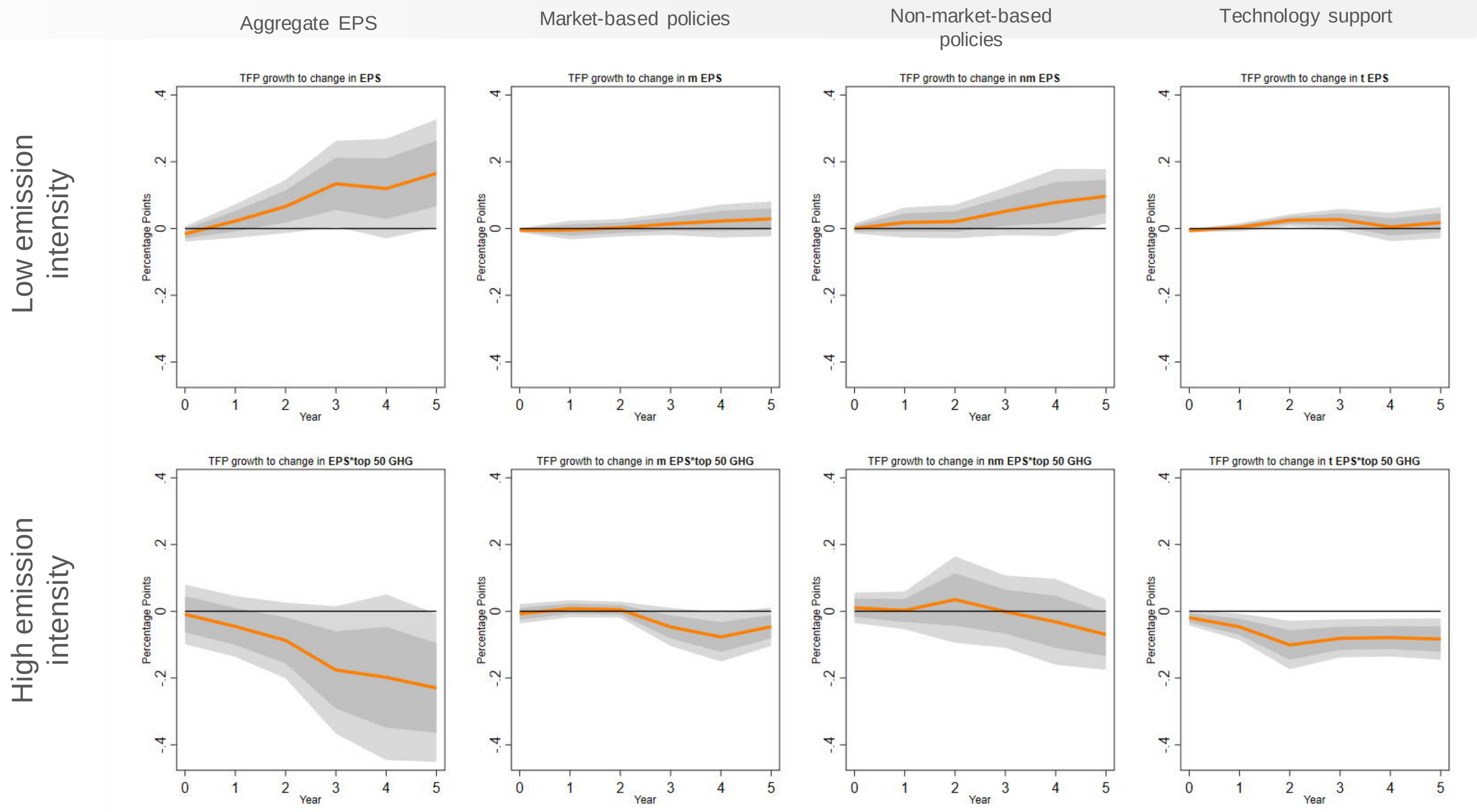
Z … firm-level controls: age, size, ROA, distance to sector frontier and TFP growth of sector frontier (before reform)

Country and time FE in aggregate analysis + firm and sector FE in firm analysis

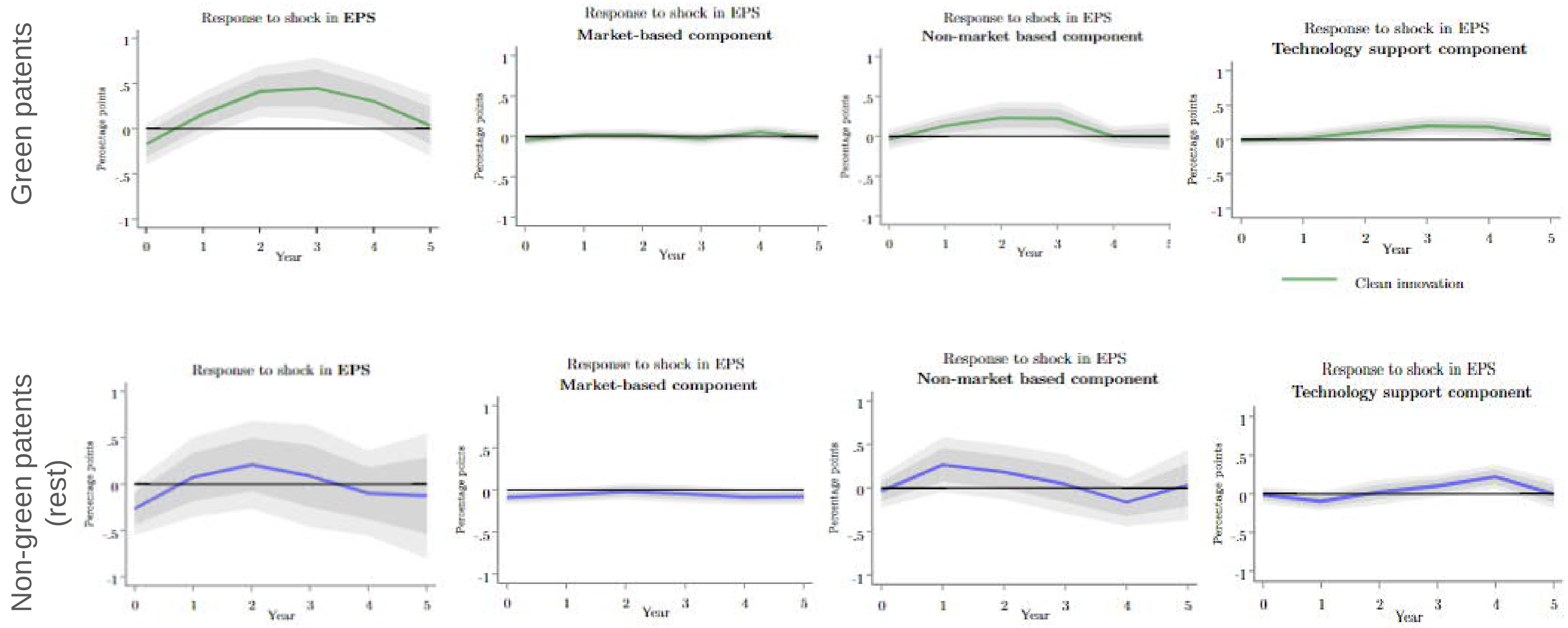
Robust (firm) clustered standard errors

Results

Aggregate results: impact on aggregate TFP growth



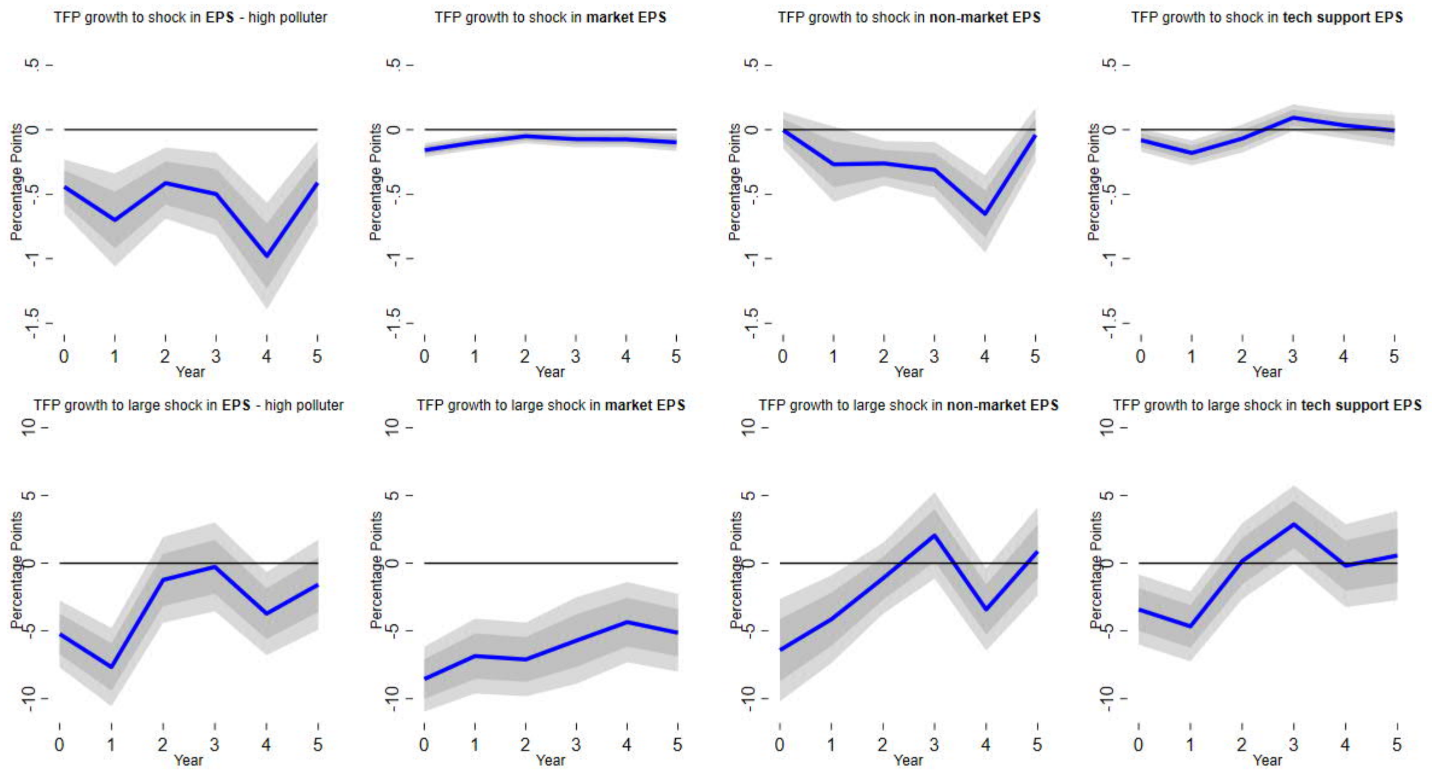
Firm-level results: Impact of a 1pp EPS tightening on patent applications (of polluting firms)



Firm-level results: Impact of a 1pp EPS tightening on TFP growth (of polluting firms)

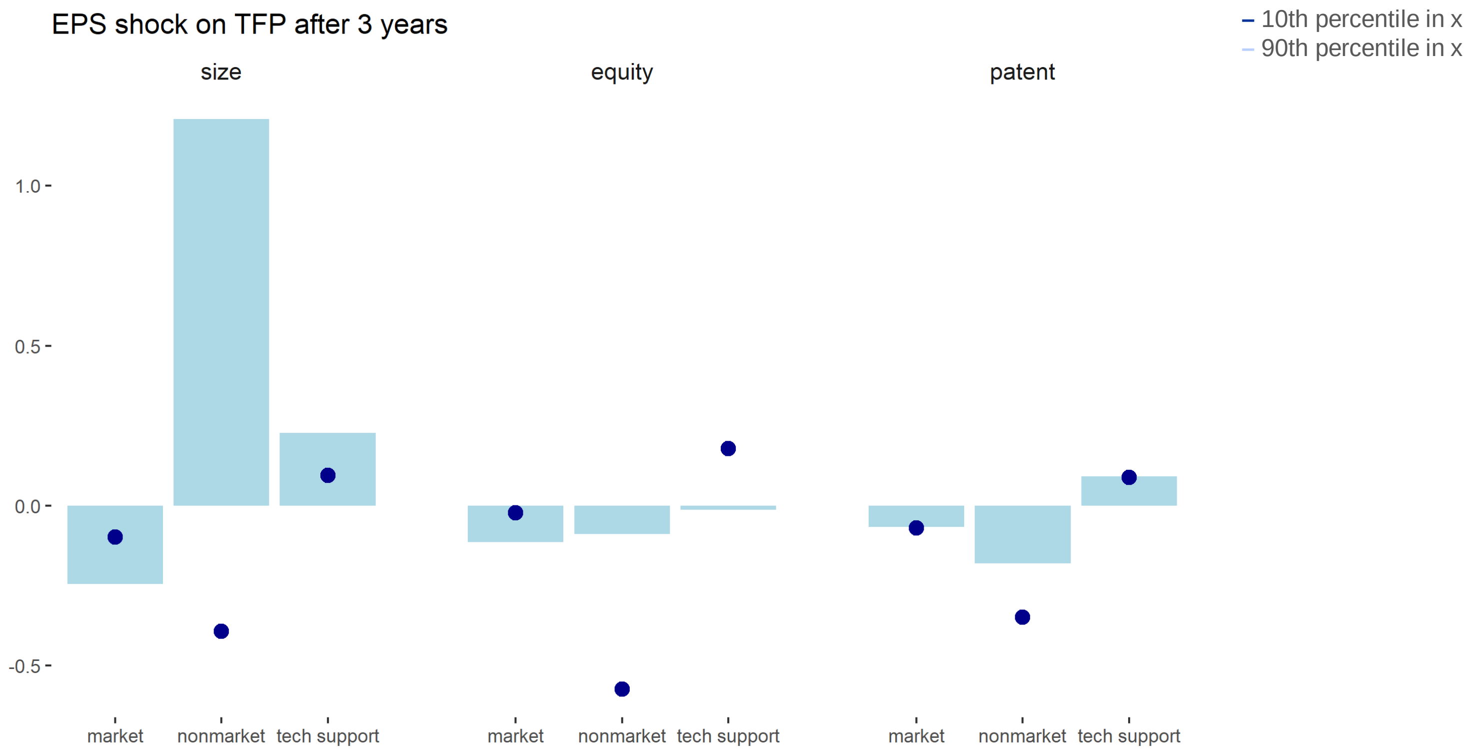
Firms with high emission intensity

Firms with high emission intensity – large shocks



other polluting definition; Lprod results

Heterogeneity across polluting firms



Conclusions

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- More stringent environmental regulation incentives green innovation (without crowding out other innovation) → The weak PH holds
- But over the medium term (up to 5 years after regulatory change) stringent environmental regulation reduces TFP growth of polluting countries and firms
  → The strong PH does not hold over the medium-term, but it could do over the long-term
- Not all policies have the same effect: market based tools are less distorting than non-market ones, but they do no boost in innovation
  - The narrow PH holds partially
  - Impact of large changes in market policies are very negative for TFP growth
- Green R&D subsidies are preferred over market policies (innovation) and non-market policies (TFP growth)
- Access to finance and experience with patenting help mitigating TFP losses of polluting firms

Appendix

Literature Review

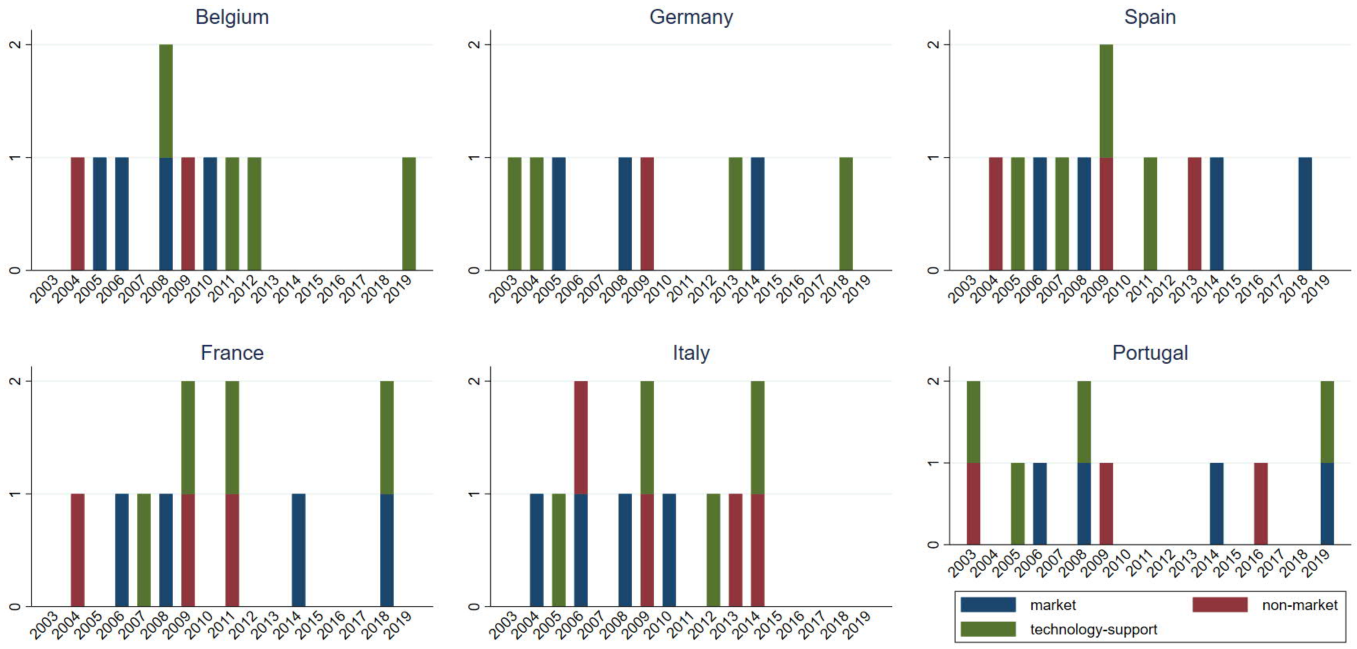
- Cohen and Tupp (2018) - Meta analysis
  “The evidence presented is inconclusive both with regards to the significance and direction of the effect”

- Albrizio, Kozluk and Zipperer (2017)
  Panel regression, identification: industry pollution dependence
  Overall productivity increase, but “at the firm-level, only a minority of the firms register productivity gains after a tightening of environmental regulation”

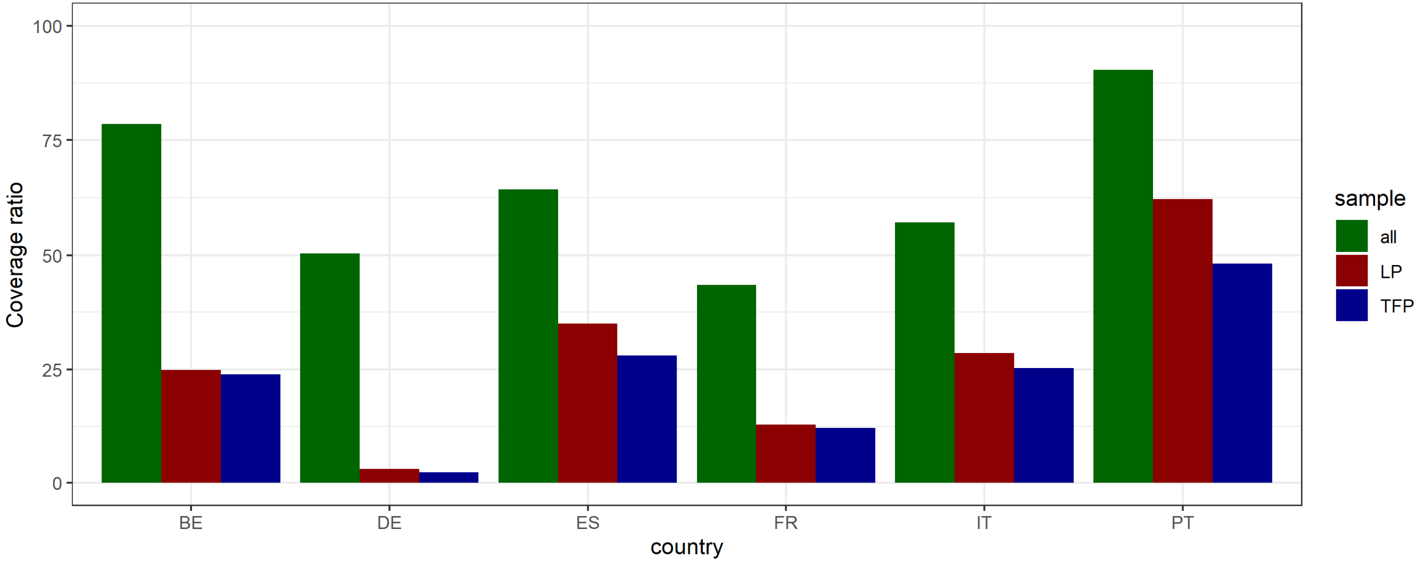
- Hille and Möbius (2019)
  Dynamic panel regression, Arellano-Bond-estimator
  “After controlling for endogeneity […] no support for the strong Porter Hypothesis can be found.”

- Weak PH: What is the impact of environmental regulation on firm-level patenting activity? (2^{nd} part of the project)

Large EPS shocks



Orbis + iBACH firm data coverage



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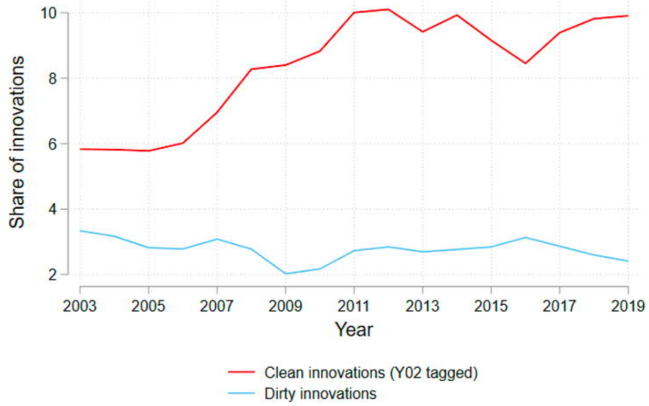
- Overview of matched sample:

Country	Clean innovations	Dirty innovations	Other innovations
BE	2486	470	29224
DE	26561	9077	247238
ES	2255	375	20738
FR	14775	4629	148584
IT	5248	2473	96773
PT	113	62	2193



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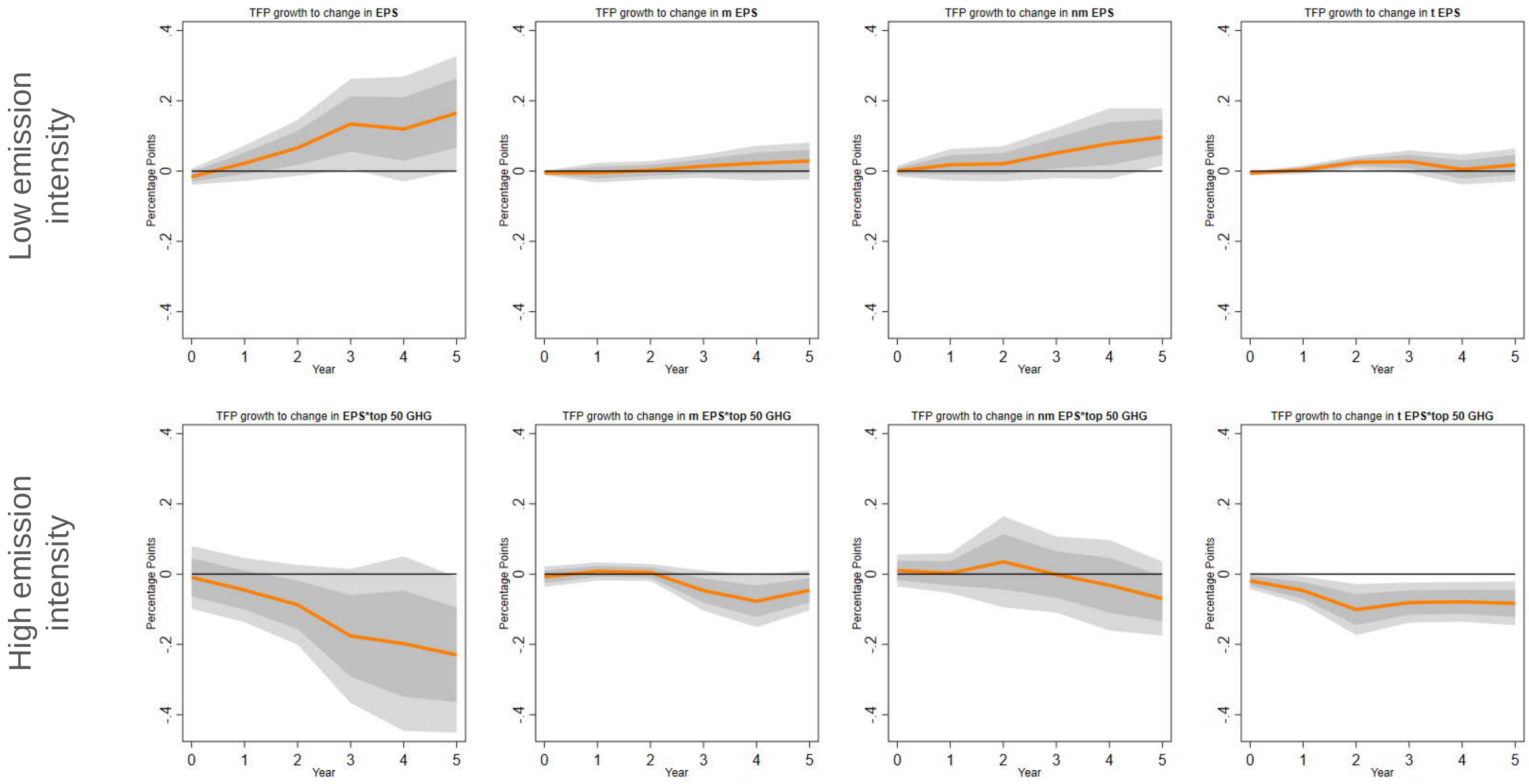
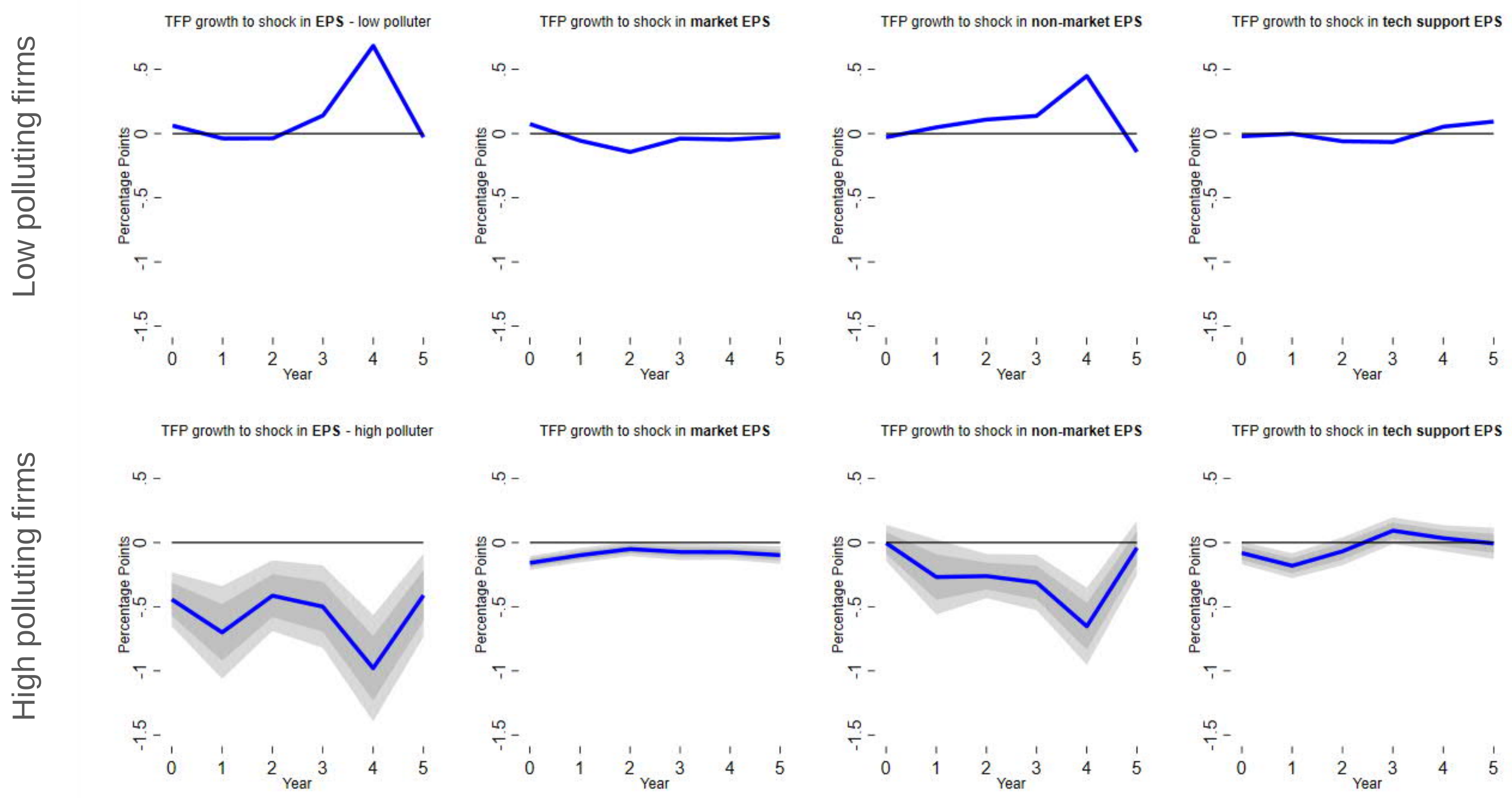
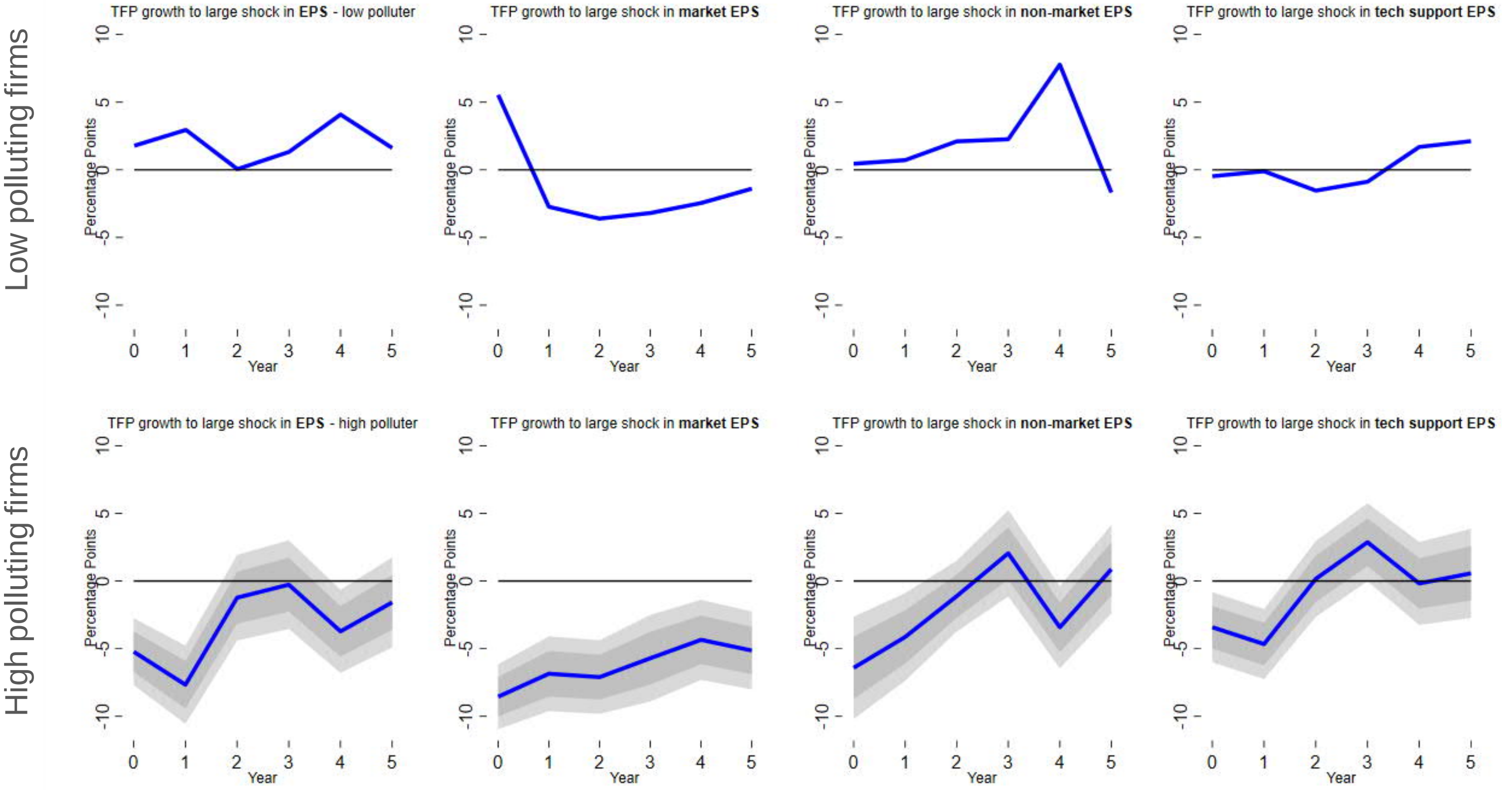
Aggregate productivity results



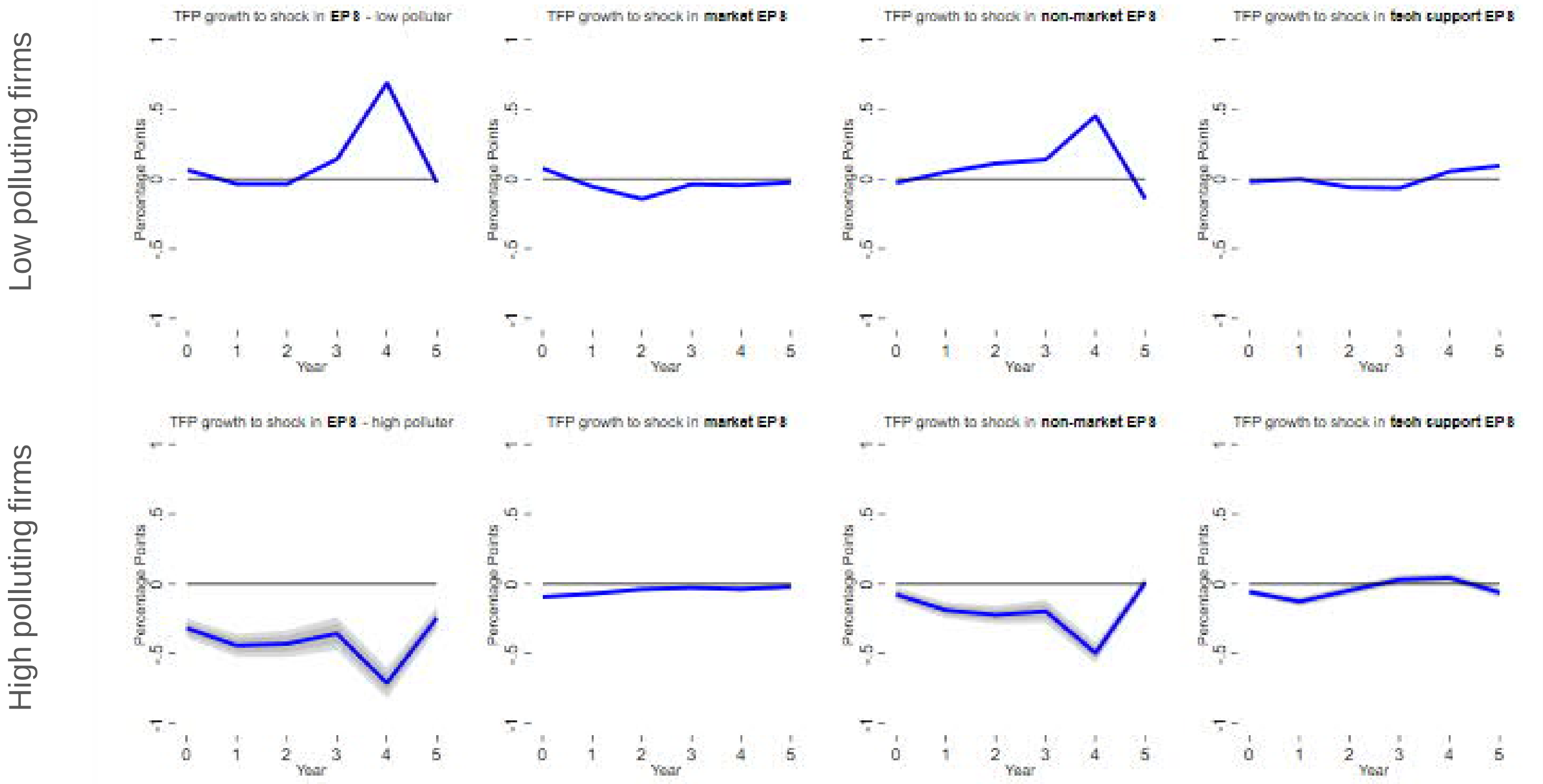
Firm-level productivity results -polluting and non-polluting firms



Firm-level effects (large shocks) – polluting and non-polluting firms



Firm-level effects (top 9 bins) – polluting and non-polluting firms



Firm-level effects (labour productivity)