Linking collaboration between organizations and environmental policy stringency to patent quality in the field of eco-technologies

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1. Introduction

Motivations

- Importance of eco-technologies and digital eco-technologies in current and future policies:

  - Digital eco-technologies play a determinant role in the current European environmental policy (EC, 2015).
  - The green transition and digital transformation are two key axes that guide future industrial policy worldwide (EC, 2020; Chen, 2023).

- Policy stringency. Environmental regulation that establishes new and more stringent standards can boost innovation (De Vries and Withagen, 2005); Popp, 2006), but the effect on innovation quality is unknown.

- Collaboration. Vast literature on how companies can benefit from collaborative innovation (Chesbrough, 2003; De Beule and Van Beveren, 2019), but limited research analyzing whether such collaboration benefits the quality of the innovative output.

Objective

- To analyze the effects of the stringency of environmental regulations and the effects of collaboration between organizations, as well as their interactions, on the quality of innovation in environmental fields.

Our contribution

- We focus on the quality of the innovative output rather than on the production innovation.

- Our study focuses on digital and environmental innovation.

- No previous empirical research has examined the impact of policy stringency and collaboration and their interaction on the quality of environmental innovation.

- An original sample of over 200k patents in the eco-technology field, with 70k in the digital eco-technology domain.

2. Literature review

2.1 The role of stringency policy in patent quality

- The weak version of the Porter Hypothesis suggests that properly designed environmental regulation stimulates certain types of innovation. A substantial number of studies favor the PH (e.g. Ambec and Barla, 2002; Martinez-Zarzoso et al., 2019).

- Most empirical studies have used the number of patents as an indicator of innovation, showing a positive relationship between stringent regulation and the number of patents. (Popp, 2006; Lannoie et al., 2011; Rubashkina et al., 2015, Fabrizi et al., 2018; Martinez-Zarzoso et al., 2019; Carrocher and Mancusi, 2021).

- Using the quantity of patents as a measure of innovation has limitations because patent quality varies significantly. Following previous literature, we focus on quality rather than quantity (Acosta. 2009; Hu et al., 2020; Pan et al., 2021; Huang et al., 2023; Wang et al., 2023).

2.2 The role of institutional collaboration on patent quality

- Through research collaboration, partners can have access to specific knowledge owned by others, which may increase the quality of the research output (Su, 2017; Lee et al., 2020).

- If firms are capable of absorbing new knowledge from partners, they can recombine it with existing knowledge, improving both innovation and quality (Zhou et al., 2021; Xu and Hu, 2024).

2.3 Interaction between stringent regulation and institutional collaboration

- Synergies between regulatory policies and collaboration networks can enhance the individual effects of each factor:

  - Institutional collaboration may favor knowledge spillovers avoiding the duplication of R&D efforts, which occurs when there is a different timing in the adoption of environmental regulation (Popp, 2006).

  - The presence of a clear regulatory framework may provide incentives and guide the direction of collaborative research (Fabrizi et al., 2018).

3. Data

- **Sources**:
  - EPO Worldwide Patent Statistical Database (PATSTAT, 2023, Spring Edition).
  - OECD Environmental Policy Stringency Index (EPS) (Kruse et al., 2022).

- **Patent families with at least one application to the EPO** (only companies).

- **Dataset**:

  1. Patents with environmental applications. (Hascic and Migotto, 2015; Favot et al., 2023): **239.288** patent families in 20 environmental fields in the period 1990-2016.

  2. Distinction between digital/non digital patents from eco-technologies (Baruffaldi et al. 2020; Martinelli et al. 2021 y Ardito et al. 2018, Bianchini, 2023). (**69,400 / 169.888** patent families).

  3. Institutional collaborations according to patent assignees (**18,797** patent families in collaboration between organizations).

  4. EPS by countries, linking them to the country of residence of each applicant.

4. Variables and Model

Variable	Definition
Dependent variable	
fpc5years	Number of forward citations within five years after the first application of the focal patent family (examiners included; self-citations excluded)
Independent variables ***Variables capturing organizational collaboration***	
collco	Dummy that takes value 1 for patents involving two or more companies (assignees)
collcoun	Dummy that takes value 1 for patents in which there is collaboration between one or more company and one or more universities.
collcogo	Dummy that takes value 1 for patents in which there is collaboration between one or more companies and any institution from the government.
collcoungo	Dummy that takes value 1 for patents involving collaboration between companies, universities and government.
Policy Stringency	
string	Average of the stringency index of the countries' assignees of each patent.
stringsqr	Square of string.
Interaction terms	
*string*collco*	Interaction between string and collco
*string*collcoun*	Interaction between string and collcoun
*string*collcogo*	Interaction between string and collcogo
string collcoungo*	Interaction between string and collcoungo
Other determinants of patent quality (patent characteristics)	
ninvent	Average number of inventors in the focal patent family
fsize	Number of patents in the family.
claims	Average number of claims of the focal patent family.
back	Number of backward patent citations
npl	Number of citations to non-patent literature.
scope	Number of different 4-digit subclasses of the IPC (Lerner, 1994).
us	Dummy that takes value 1 if the patent family contains a patent with US priority.
jp	Dummy that takes value 1 if the patent family contains a patent with JP priority.
Other control variables: sector dummies, year dummies.	

Empirical model

$$fpc5years_i = \exp\Bigg(\alpha_0 + \sum_{\mathrm{k}=1}^{j} \alpha_j\, coll_i + \mu_1 stringency_i + \ \mu_2 stringency_i^2$$

$$+ \sum_{\mathrm{k}=1}^{K} \lambda_k\, coll * stringency_i + \beta_1 ninvent_i + \beta_2 fsize_i + \beta_3 mclaim_i$$

$$+ \ \beta_4 bt_i + \ \beta_5 npl_i + \ \beta_6 scope_i + \ \beta_7 us_i + \ \beta_8 jp_i + \sum_{n=1}^{\mathrm{N}} \theta_n\, sector_i$$

$$+ \sum_{t=1}^{\mathrm{T}} \varphi_t\, year_i + \varepsilon_i\Bigg)$$

Estimation: Poisson pseudo maximum likelihood (PPML) (Wooldridge, 2010; Santos Silva and Tenreyro, 2011)

5. Results

	All patents				Deco=1	Deco=0
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
collco	0.4915***	0.2345***		0.2142***	0.3001***	0.0004
	(0.0246)	(0.0240)		(0.0703)	(0.1044)	(0.0759)
collcoun	0.2245***	0.0072		-0.2390	-0.3467	-0.3834**
	(0.0833)	(0.0687)		(0.1495)	(0.2975)	(0.1816)
collcogo	-0.0943	-0.1903**		-0.7739***	-1.0645**	-0.7281***
	(0.0820)	(0.0879)		(0.2412)	(0.5424)	(0.2642)
collcoungo	0.2105	-0.2393		0.2102	1.0845	-0.6714
	(0.2925)	(0.2663)		(0.5197)	(0.8464)	(0.5643)
string	0.4389***		0.5885***	0.5702***	0.5654***	0.3479***
	(0.0441)		(0.0466)	(0.0466)	(0.0837)	(0.0462)
stringsqr	-0.1754***		-0.1899***	-0.1869***	-0.1903***	-0.1173***
	(0.0110)		(0.0114)	(0.0114)	(0.0197)	(0.0117)
*string*collco*				0.0190	0.0051	0.0572*
				(0.0310)	(0.0509)	(0.0311)
*string*collcoun*				0.1281*	0.2295	0.1456**
				(0.0727)	(0.1768)	(0.0728)
*string*collcogo*				0.2453**	0.4397	0.2025
				(0.1188)	(0.2812)	(0.1247)
string collcoungo*				-0.1315	-0.2432	0.0131
				(0.1932)	(0.3642)	(0.1777)
Patent charact.	YES	YES	YES	YES	YES	YES
Sector dummies	YES	YES	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES	YES	YES
Nº Observations	239,288	239,288	239,288	239,288	69,400	169,888
Log P-likelihood	-499,297.21	-485,992.17	-466,303.46	-465,485.86	-191,692.84	-266,700.92

Dependent variables: Forward citations with a 5-year window, citations by examiners included, self-citations excluded.
PPML: Poisson pseudo maximum likelihood.
$*$ $p < 0.10$; $**$ $p < 0.05$; $***$ $p < 0.01$.

5. Conclusions

Effect of institutional collaboration on patent quality

- Collaboration between companies positively affects patent quality compared to the development of patents by single firms (incidence ratio of 1.239).
- Other forms of collaboration have no effect or even a negative impact on patent quality.

Effect of policy stringency on patent quality

- Inverted U-shaped effect of policy stringency on patent quality, with an extreme point of 1.5.

Moderating effect of policy stringency on collaboration

- The negative effect of collaborating with government is moderated by the stringency policy.
- The effect of collaborating with universities becomes significant when it interacts with the level of stringency.

Policy implications

- The best strategy to produce environmental patents of better quality is through collaboration between companies. Incentives that help foster business collaboration can favor the increase of patent quality in the field of environmental technologies.

- Patent quality seems to be triggered by the stringency of environmental policy, but until a certain point, from which patent quality starts to decrease.

Limitations and future research

- Patents and citations as measures of innovation and quality/impact.

- Technological distance between institutions involved in the innovation process could be the reason for the lack of significance of institutional collaboration other than between companies.

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