Harnessing green energy patents and spillovers for regional sustainability: insights from European ecosystems

Eben 2025. Dinamizando el Cambio para un Futuro Responsable, Ético y Centrado en las Personas

(21-23th May 25 Santiago de Compostela, Spain)

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1. Introduction

Motivations

- CO2 emissions are the primary contributor to global climate change, with 70% of which are linked to excessive energy consumption (IEA, 2017).

- Green technological progress is a key factor in reducing energy intensity and environmental impact (Bianchini et al., 2022; Pan et al., 2021; Naqvi 2021; Tobelmann and Wendler 2020; Wang et al. 2020; Ghisetti and Quatraro 2017).

- But it is unclear whether digital technologies can help to tackle the problem (Rolnick et al. 2019) or worsen environmental problems (Bianchini et al., 2022).

- Little evidence on the effects of the twin transition on emissions. Bianchini et al. (2022) is the only attempt, but he neglects knowledge spillovers and is not focused on energy technologies.

- Knowledge spillovers are a key source of technological progress (Romer, 1986; 1990), but studies linking innovation and CO2 emissions often ignore them.

Objective

To analyse the effects of the use of eco-technological knowledge and specialisation in digital eco-technologies in energy domains on CO_2 emissions at the regional level.

Our contribution

- We provide quantitative evidence on this topic at the regional level.

- We include the effect of national and international knowledge spillovers.

- We rely on an original sample of over 140k patents in the energy eco-technology domain, of which 16K are related to digital domains.

2. Literature review and hypotheses

2.1. Innovation, knowledge spillovers and emissions

Green energy technologies

- Implementing green technologies can reduce energy use and promote resource conservation and recycling, which will directly affect energy intensity (Chakraborty and Mazzanti, 2020, Pan et al., 2021) and, thus, CO_2 emissions.

H1: The access to internal eco-tech knowledge in the region reduces regional CO_2 emissions.

Digital technologies

- Digital technologies may help to tackle environmental problems (see, e.g., Rolnick et al. 2019).
- But they can increase emissions for several reasons: intensive energy consumption (Dusik et al. 2018; Jones 2018; Strubell et al. 2019); most of the materials cannot be re-cycled or re-used, leading to a technological dead end and waste management issues, hence increasing emissions (Shift Project 2019; Kunkel and Matthess 2020).

H2: The regional specialization in digital energy eco-technologies increases regional CO_2 emissions.

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Knowledge spillovers and CO2 emissions

- Knowledge spillovers can expand the use of existing green technologies and improve the utilization of green technologies, thereby affecting energy efficiency (Chakraborty and Mazzanti, 2020) and thus CO2 emissions.

- A region that absorbs external knowledge increases its available knowledge stock and stimulates further innovation (Pan et al., 2021), which in turn could lead to a reduction in CO2 emissions.

- The effects of national or international knowledge spillovers may differ due to increased technological, cultural, geographic, and linguistic distance across countries that can hinder the absorption, and thus the effects of external knowledge.

  H3: National knowledge spillovers of energy eco-technologies reduce regional CO2 emissions.

  H4: International knowledge spillovers of energy eco-technologies reduce regional CO2 emissions.

Figure 1. Theoretical model on the effect of energy eco-technologies knowledge (En-ecotech)
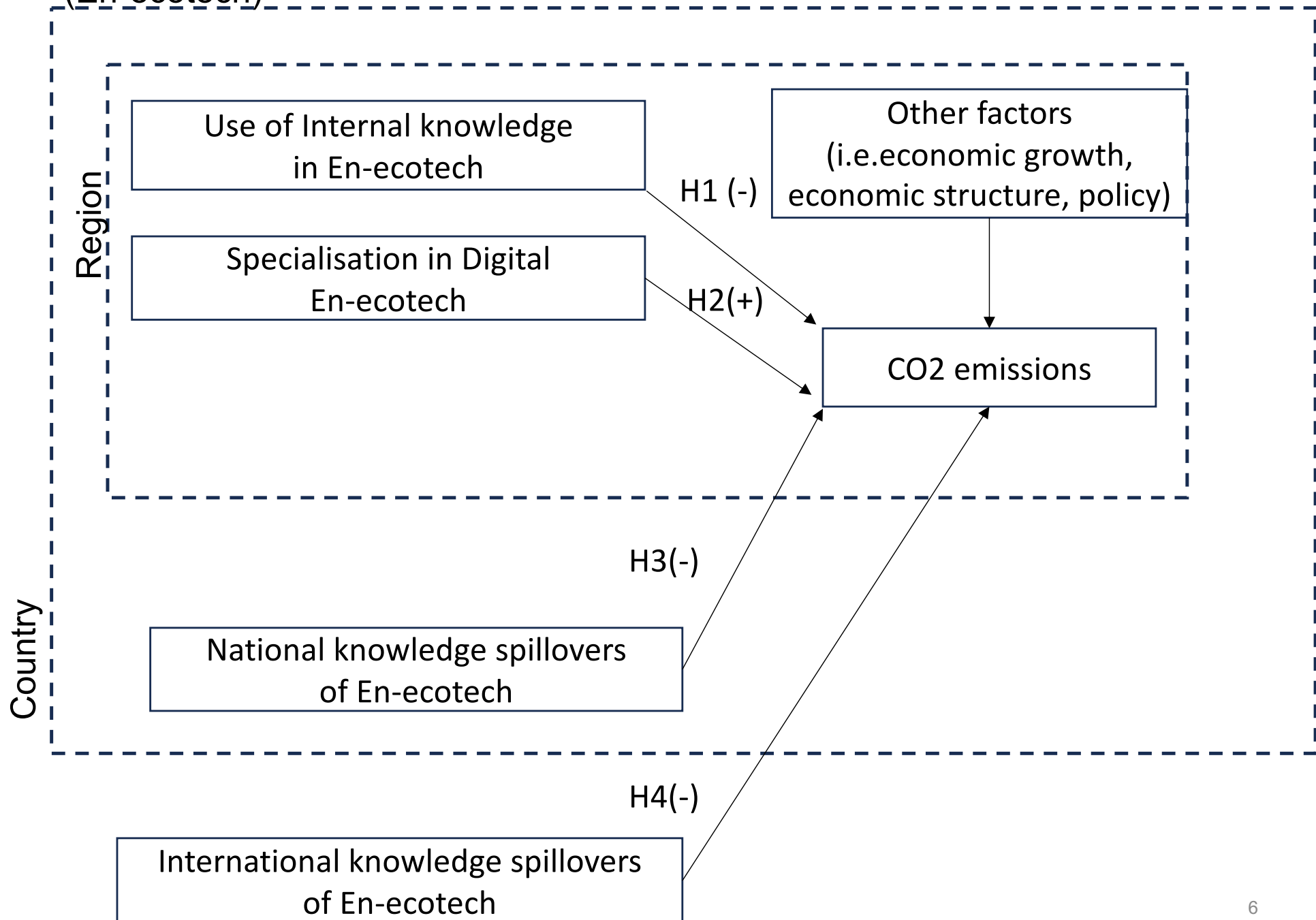
3. Data

- Patent families with at least one application to the EPO.
- Unit of observation: NUTS 2 regions in Europe. 5.507 observations: 197 regions of 19 countries for the period 1990-2022 (unbalanced panel).

Dataset:

1) We gathered patents in energy with environmental applications (OECD, 2022). 140,666 patents.
2) From these, we identified whether they are also related to digital domains (Baruffaldi et al. 2020; Martinelli et al. 2021; Ardito et al. 2018, Bianchini, 2023). 16,937 patents (12,04% of total energy eco-patents). Steps 1&2: IPC/CPC codes and/or keywords.
3) We regionalised all patents by NUT2 in EU (or by countries if non-EU).
4) For each EU-region, we computed the internal, national, and international weighted stocks of knowledge. Perpetual inventory method. Weight: share of internal, national, or international backward citations over the total number of backward citations, respectively (Mancussi, 2008).
5) Retrieve control variables.

Sources: EPO Worldwide Patent Statistical Database (PATSTAT, 2023 version). Control variables: Eurostat, ARDECO, others.

4. Variables and model

Variable	Description	Source
Dependent var.		
Co2_emissions	Log CO2 per capita	EDGAR & ARDECO
Main independent var. (Three lags with respect to the dependent variable)		
l_Internal_stock_pc	Stock per capita of energy eco-patents within region i (logs)	PATSTAT
l_National_stock_pc	Stock per capita of energy eco-patents in other regions within the same country (logs)	
l_International_stock_pc	Stock per capita of energy eco-patents in other countries (logs)	
Specialisation_deco	(Stock of digital eco-patents within region ij/total stock of eco-patents within the region)/ (stock of digital eco-patents within country j/total stock of eco-patents within the country j) (Without weights)	
Control var.		
GDPpc_growth	Growth rate of GDP per capita	ARDECO
l_gdppc (and sqr)	GDP per capita at constant prices 2005 (logs).	
Industry_share	Share of industry value added to regional GDP (%)	
Renewable	Renewable energy consumption (% of total final energy consumption). Country	World Bank
Stringency (and sqr)	Indicator of stringency of environmental policy with three lags. Ranges from 0 to 6 (highest). Country	OECD

Models:
- Multilevel specification. Level 1: region; Level 2: country
- OLS models (with RSE, including year, country and sectors dummies.

5. Results

Dep:ln_co2_pc	MULTILEVEL MODELS				OLS		
	Total energy.	Digital energy	No digital energy		Total energy	Digital energy	No digital energy
	1	2	3		4	5	6
	Coef.	Coef..	Coef..		Coef..	Coef.	Coef.
L3.l_internal_stock_pc	-0.0260	-0.0785	-0.0082		-0.0281	-0.0815	-0.0095
L3.l_national_stock_pc	-0.1904***	-0.0965***	-0.1925***		-0.1922***	-0.0966***	-0.1942***
L3.l_international_stock_pc	-0.0656***	-0.0535***	-0.0675***		-0.0658***	-0.0534***	-0.0677***
L3.Specialisation_deco	0.0404**	0.0460***	0.0403**		0.0408***	0.0465***	0.0407***
gdppcgrowth	0.0028	0.0070	0.0028		0.0028	0.0070	0.0029
l_gdppc	2.6782*	0.1638	2.7431*		2.7281**	0.1848	2.7970**
l_gdppc_sqr	-0.1381*	-0.0176	-0.1416**		-0.1415**	-0.0197	-0.1452**
Industry_share	0.0363***	0.0279***	0.0363***		0.0364***	0.0279***	0.0363***
Renewable	-0.0162*	-0.0203**	-0.0168*		-0.0184	-0.0243**	-0.0191
strigencyL3	-0.6132***	-0.4036**	-0.6101***		-0.6297***	-0.4164**	-0.6264***
strigencyL3_sqr	0.0916***	0.0557*	0.0909***		0.0931***	0.0569*	0.0923***
_cons	-18.3991***	-5.9839	-18.6914***		-18.7041***	-5.9056	-18.9991***
lns1_1_1							
_cons	0.0172	-0.0196	0.0151				
lnsig_e							
_cons	0.4146***	0.4263***	0.4147***				
Obs.	5507	5507	5507	Obs.	5507	5507	5507
N groups	19	19	19	R	0.3777	0.3630	0.3776
Log likelihood	-10139.79	-10203.03	-10140.24	R_A			
Wald chi2(7)	412.96***	278.44***	411.99***	Log likelihood	-10087.83	-10151.93	-10088.31
chi2_c	1634.90***	1541.90***	1635.43***				

Std. errors not displayed for simplicity.

5. Conclusions

- The use of internal energy eco-tech knowledge does not affect CO_2 emissions, but external eco-tech knowledge spillovers decreases emissions (both national and international). (H1 not supported; H2,H3 supported).

- The size of the effect of external spillovers is similar between digital and non digital eco-tech, although the impact is slightly lower for the former.

- Specialisation in digital energy eco-technologies increases CO_2 emissions (H4 supported).

- GDP growth does not affect CO_2 emissions (maybe because using total GDP growth instead of industrial GDP growth?)

- Renewable energy consumption reduces emissions and the industry share in the regional GVA increases emissions. Expected.

- Policy stringency reduces CO_2 emissions, although the effect is U-shaped.

Policy implications

- Since the use of external knowledge (national and international) is crucial for reducing emissions, we derive two implications:

  1) Increasing national and international stocks, which could demand a joint effort involving policies and instruments developed by countries and EU governments.

  2) Improving accessibility to external knowledge pools. For example, by enhancing researchers mobility and collaboration.

- For now, the potential of the digital technologies to decrease CO_2 emissions has not been unlocked and our results suggest that their environmental costs still exceed their benefits in terms of CO_2 emissions.

- Keep fostering renewable energy consumption.
- Implement stringent environmental policies, but only up to a certain point.

Limitations and extensions

-Replace GDP growth by industrial GDP growth in our models.
-Endogeneity?

Many thanks