

Public R&D and green knowledge diffusion

Evidence from patent citation data

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Paper sketch

- Empirical investigation of the relationship between public R&D and green knowledge diffusion

Paper idea and findings

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- Positive effect of public R&D on the rate of citations received by green patents ($\uparrow 1\% \text{ R\&D} \Rightarrow \approx .1\% \text{ more citations}$)
- Public R&D as a lever for hybridization of traditional innovation processes and for technological diversification

Background and hypotheses

The two blocks of the paper:

GT knowledge

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Public R&D

- Basic research

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GT features

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- Systemic nature and general purpose content (Ghisetti et al., 2015).
Higher complexity and novelty (Quatraro and Scandura, 2019).
Combination of more heterogeneous and distant knowledge than other innovations to be performed (Renning and Rammer, 2009; Nemet, 2012; Horbach et al., 2013; Benson and Magee, 2014). Mixed inventor teams with ability in creatively recombining extant knowledge (Orsatti et al., 2020).

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- Green occupations exhibit a **stronger intensity of high-level cognitive skills** compared to non-green jobs (Consoli et al., 2016; Vona et al., 2017, 2018).
- **High spatial concentration of high-skill intensive occupations** drives the local generation of GTs (Orsatti et al., forthcoming).

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- ➔ **Uniqueness of GT knowledge ⇒ Public R&D as a lever for its generation and diffusion**

Restoring efficiency and fostering GT diffusion

HP1. *Increasing public R&D fosters the diffusion of GT knowledge*

Working hypotheses

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Technological diversification

HP3. *Increasing public R&D enhances the technological distance between green technologies and technologies using green knowledge*

Empirical design

Patent level analysis: 16,091 green patents applied at the European Patent Office (EPO) between 1980 and 1984 by inventors residing in 16 OECD countries

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- Patent-country matching on inventor address

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- Green patents: WIPO “IPC Green Inventory” + OECD “Indicator of Environmental Technologies” classifications
- Patent-country matching on inventor address
- Patent citations \Rightarrow technological diffusion (Trajtenberg, 1990) measured over 1981-1988 (EP-EP pairs)

Government appropriation or outlays budget for R&D (GBAORD) by socio economic objective (SEO)

- OECD-Eurostat international data collection on resources devoted to R&D funded by central governments (budget-based data)
- 16 OECD countries (1981-1988)
- 15 SEOs: among them, we exploit info on energy, industrial production and technology, health, telecommunication and other infrastructures, transport.

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- Two-step matching:
 - SEOs to NACE rev. 2 sectors (Stancík, 2012)
 - NACE codes to IPC classes (Van Looy et al., 2014)

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Endogeneity issues

The unexpected occurrence of the Chernobyl nuclear accident in 1986 as an exogenous shock for public R&D decisions in the energy domain.

The context

- Strong reliance and vast investments in nuclear power to reduce oil dependence
- Nuclear power vital for the architecture of alternative technologies (i.e. renewables)

Identification strategy

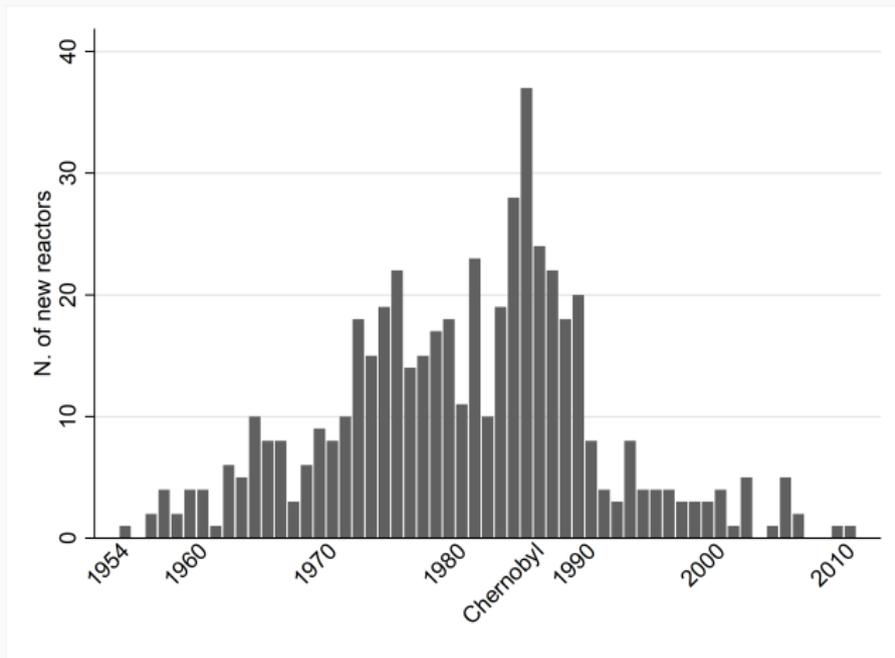


Figure 1: Number of new nuclear reactors connected to the grid (1954-2015)

Notes: The figure plots the number of new nuclear reactors connected to the grid worldwide (1954-2015). *Source:* Author's elaboration on IAEA (2016) data.

The unexpected occurrence of the Chernobyl nuclear accident in 1986 as an exogenous shock for public R&D decisions in the energy domain.

Reaction to the accident

- Public opinion pushed governments to promptly intervene against nuclear power
(e.g. 1987 referendum in Italy)
- ↳ Reduction of the public R&D support for all alternative-to-fossil energy sources \Rightarrow negative exogenous shock

Identification strategy

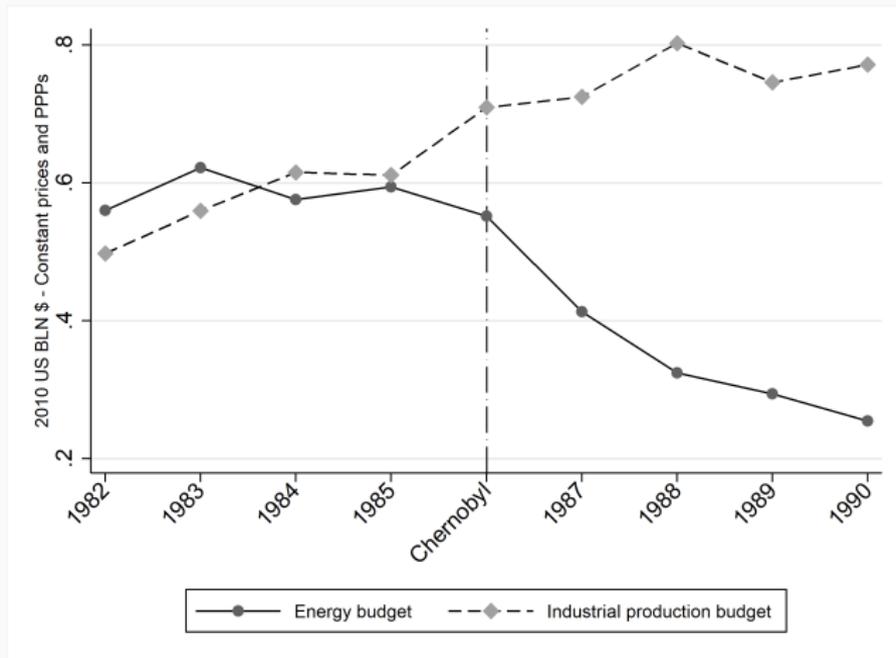


Figure 2: GBAORD average level (Energy vs. Ind. production, 1982-1990)

Notes: The figure plots the average level (in 2010 BLN US\$, constant-prices and PPPs) of energy-related GBAORD and industrial production-related GBAORD (dashed line) in selected EU countries between 1982-1990. *Source:* Author's elaboration on OECD (2017) data.

Empirical models

To measure the effect of a change in GBAORD on the rate and the direction of green knowledge diffusion, we estimate three specifications of a two-stage least square model (2SLS).

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FIRST STAGE: we estimate the level of GBAORD with a linear probability model in a DiD configuration

$$GBAORD_{i,t} = \alpha_i + \delta_t + \beta_1 POST_{i,t} + \beta_2 ENERGY_i \times POST_{i,t} + \Omega'_{i,t} \Gamma + \epsilon_{i,t}$$

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SECOND STAGE: Effect of (instrumented) *GBAORD* on green knowledge diffusion

$$Y_{i,t} = \alpha_i + \delta_t + \beta_1 POST_{i,t} + \beta_2 \widehat{GBAORD}_{i,t} + \Omega'_{i,t} \Gamma + \epsilon_{i,t}$$

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Dependent variables ($Y_{i,t}$):

- Number of citations received
- Number of citations received from non-green patents
- Average technological distance of citations received
 - Symmetric distance metric originally proposed by Akcigit et al. (2016), based on patent citation co-occurrences between IPC classes.

$$Y_{i,t} = \alpha_i + \delta_t + \beta_1 POST_{i,t} + \beta_2 \widehat{GBAORD}_{i,t} + \Omega'_{i,t} \Gamma + \epsilon_{i,t}$$

Other variables:

- α_i : patent fixed effects
- δ_t : year fixed effects
- $POST_{i,t}$: post-1986 indicator
- Further controls ($\Omega'_{i,t}$):
 - intramural business R&D expenditures (BERD)
 - emission intensity
 - oil price, adjusted for inflation

Test for dynamic effects of the accident on GBAORD

$$GBAORD_{it} = \sum_{k=-3}^2 \beta_k \mathbf{1}_{\{l_{it}=k\}} + \beta^{All} \times Post_{it} + \alpha_i + \delta_t + \varepsilon_{it}$$

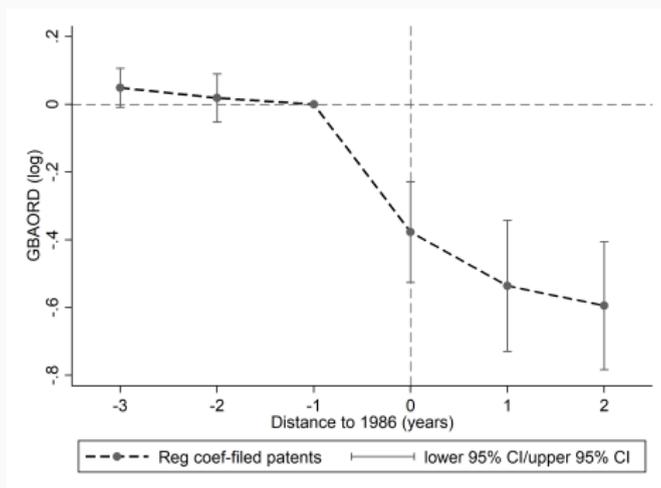


Figure 3: The dynamic effect of the Chernobyl nuclear accident on GBAORD

Notes: The figure reports point estimates of the dynamic effects associated with lags and leads around the Chernobyl accident (i.e., the set of β coefficients in the equation).

Table 1: The effect of GBAORD on GT knowledge diffusion

FIRST STAGE RESULTS (Dep var: GBAORD (log))			
Energy×Post		-0.404*** (0.004)	
F-stat		16.27	
		IV RESULTS	
	Tot citations (log)	Dirty citations (log)	Tech distance
GBAORD (log)	0.066*** (0.016)	0.070*** (0.010)	0.008*** (0.000)
BERD (log)	-0.00036 (0.020)	-0.019 (0.015)	-0.0020*** (0.001)
Emission intensity	-0.082*** (0.015)	-0.060*** (0.010)	-0.0080*** (0.000)
Oil price (log)	0.14*** (0.020)	0.036** (0.015)	-0.00049 (0.000)
Post-1986	YES	YES	YES
Patent FE	YES	YES	YES
Year FE	YES	YES	YES
N	99,002	99,002	99,002

Notes: Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

Conclusions

Summary

- The Chernobyl accident strongly affected energy-related public R&D
- Public R&D as a driver of green knowledge diffusion
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- Public R&D as a driver of green knowledge diffusion
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→ immediate and decisive intervention required

Further implications and future research in the GT domain

- Technological niches with high breakthrough potential to be systematically targeted
- The management of publicly-funded R&D projects is a relevant topic
- How does public R&D coordinate with private R&D for GTs?

Questions?

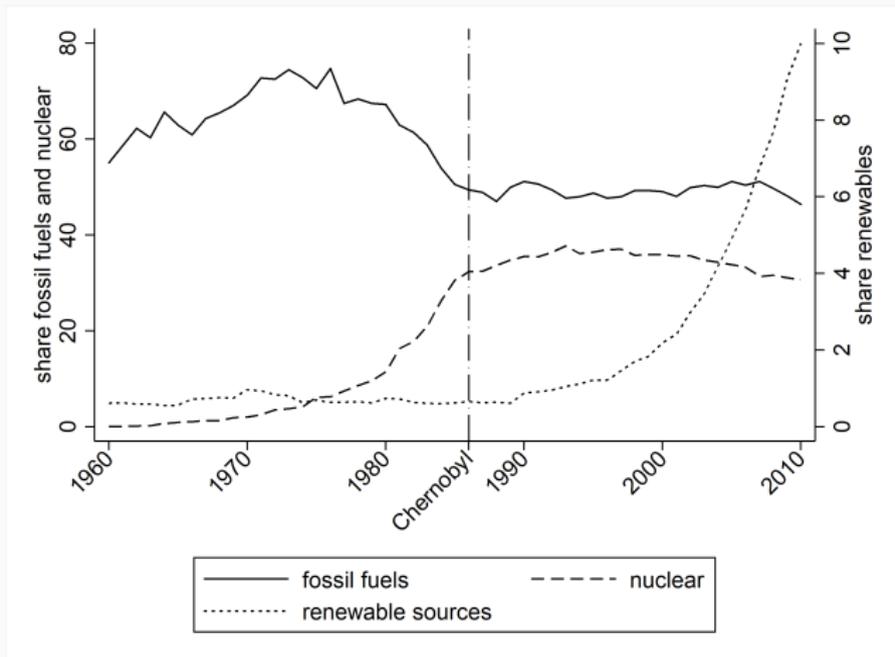


Figure 4: Electricity production by source, shares (EU, 1960-2010)

Notes: The figure plots the share contribution of fossil fuels, nuclear and renewables to electricity production in EU countries (1960-2010). Hydroelectric source not considered. *Source:* Author's elaboration on World Bank (2017) data.

Backup slides

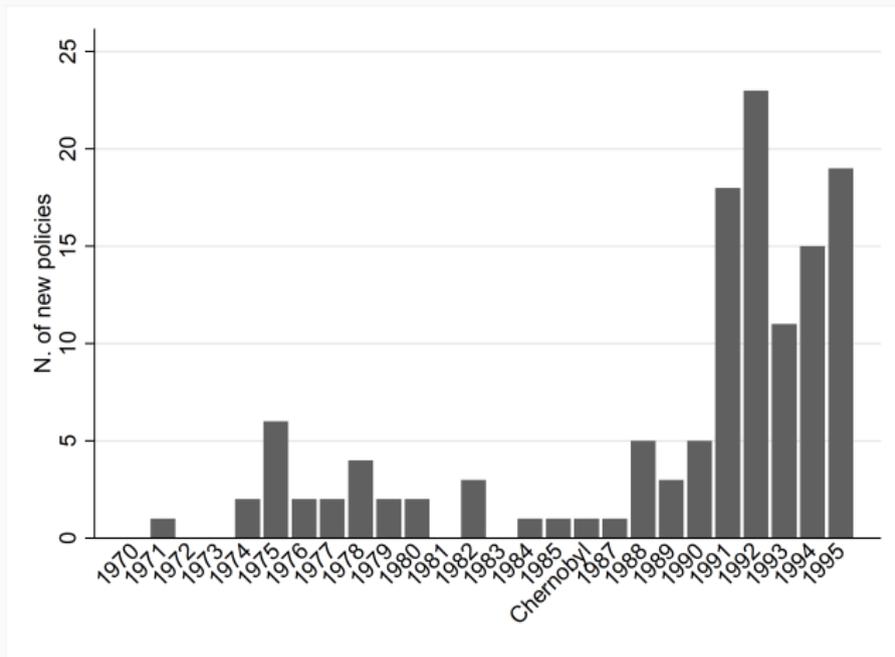


Figure 5: Number of new environmental policies (IEA countries, 1970-1995)

Notes: The graph reports the number of new environmental policy tools implemented by IEA Member Countries between 1970 and 1995.

Source: Author's elaboration on IEA (2017) data.

Backup slides

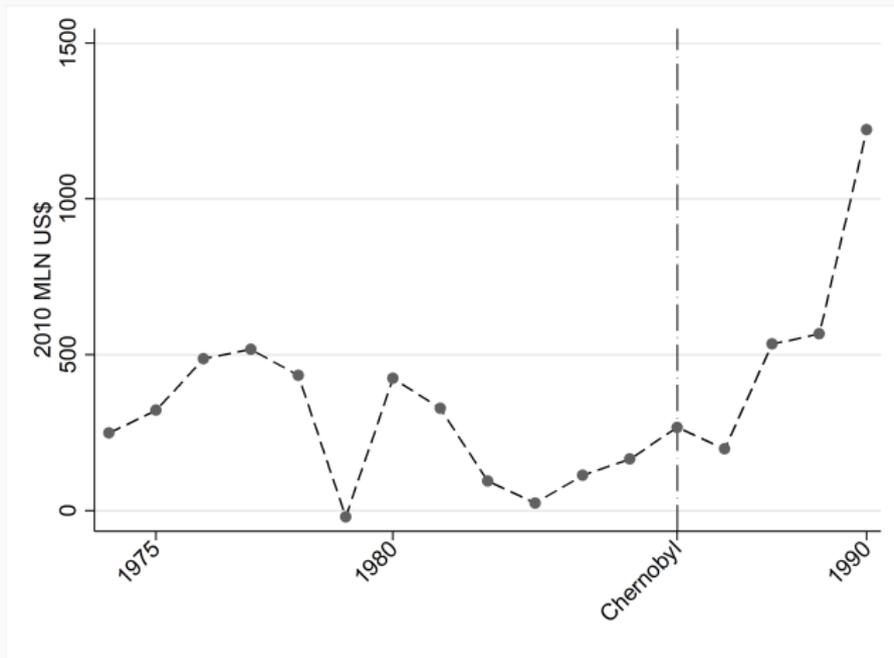


Figure 6: US-Gov energy-R&D expenditure: difference between fossil-fuels and renewables (1974-1990)

Notes: The figure plots the difference (in 2010 MLN USD) between US government R&D in fossil fuels and in renewable sources between 1974 and 1990. *Source:* Author's elaboration on OECD/IEA (2017) data.

Backup slides

To build a measure of technological distance between patents we rely on the symmetric distance metric originally proposed by Akcigit et al. (2016). This measure is based on patent citation co-occurrences between IPC classes (four digits). Our aim here is to measure the technological distance between the focal patents and their citing patents. Let consider two IPC classes i and j , their distance $d(i, j)$ is measured as follows:

$$d(i, j) \equiv 1 - \frac{\#(i \cap j)}{\#(i \cup j)}$$

where $0 \leq d(i, j) \leq 1$; $(i \cap j)$ is the number of patents that cite patents from technology classes i and j simultaneously, while $(i \cup j)$ is the number of patents that cite technology class i and/or j .

To measure the technological distance between citing patents and our focal green (cited) patents, we calculate $d(i, j)$ for all the IPC pairs formed by citing IPC classes and IPC classes contained in the focal patents. For each focal patent i at time t , we then take the average technological distance from its citing patents as our dependent variable.

Table 2: Summary statistics

Variable	Obs	Mean	SD	Min	Max
Tot citations (log)	99,002	.1814	.3844	0	3.2189
Dirty citations (log)	99,002	.0885	.2704	0	2.8332
Tech distance	99,002	.0082	.0158	0	.1555
GBAORD (log)	99,002	6.3168	1.1818	.4324	11.1029
BERD (log)	99,002	10.5441	1.4649	4.1455	11.9509
Emission intensity	99,002	4.5652	1.5652	1.6354	6.7713
Oil price (log)	99,002	3.9192	.3789	3.4446	4.5626

TABLE 5: INCLUSION OF GERMANY-INVENTED PATENTS

PANEL A: FIRST STAGE RESULTS						
	Exclusion Emission Intensity		Inclusion GBAORD Env			
	Dependent variable: GBAORD (log)		Dependent variable: GBAORD Env			
	(a)		(b)			
Energy × Post	-0.487***		-0.491***			
	(0.0035)		(0.0038)			
Controls	YES		YES			
Patent FE	YES		YES			
Year FE	YES		YES			
Observations	146,483		146,483			
Adjusted R ²	0.290		0.311			
F-stat	25.23		25.29			

PANEL B: SECOND STAGE RESULTS						
	Dependent variables:					
	Tot cites (log)	Dirty cites (log)	Tech distance	Tot cites (log)	Dirty cites (log)	Tech distance
	(a.I)	(a.II)	(a.III)	(b.I)	(b.II)	(b.III)
GBAORD (log)	0.056***	0.057***	0.006***	0.056***	0.057***	0.006***
	(0.011)	(0.0068)	(0.00017)	(0.011)	(0.0068)	(0.00017)
Post Chernobyl	0.196***	0.082***	0.006***	0.198***	0.086***	0.006***
	(0.016)	(0.012)	(0.00037)	(0.016)	(0.012)	(0.00038)
BERD (log)	0.009	-0.016	-0.003***	0.003	-0.027*	-0.004***
	(0.020)	(0.014)	(0.00059)	(0.021)	(0.015)	(0.00060)
Oil price (log)	0.100***	0.009	-0.004***	0.099***	0.006	-0.005***
	(0.015)	(0.012)	(0.00034)	(0.015)	(0.012)	(0.00034)
GBAORD Env				0.006	0.011***	0.001***
				(0.0046)	(0.0034)	(0.00013)
Patent FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Observations	146,483	146,483	146,483	146,483	146,483	146,483

Notes: Panel A reports the first stage results. Column (a) excludes Emission Intensity from the set of control variables; column (b) substitutes Emission Intensity with GBAORD related to the environment (GBAORD env). Panel B reports the second stage results. Columns a.I, a.II and a.III are based on the first stage reported in Panel A, column a. Columns b.I, b.II and b.III are based on the first stage reported in Panel A, column b. All the models are estimated on the sample used in the main analysis, extended also to patents invented in Germany over the period 1980-1984. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

TABLE 6: EXCLUSION OF US- AND UK-INVENTED PATENTS

PANEL A: FIRST STAGE RESULTS	
Dependent variable: GBAORD (log)	
(I)	
Energy \times Post	-0.614*** (0.0073)
Controls	YES
Patent FE	YES
Year FE	YES
Observations	36,724
Adj. R^2	0.427
F-stat	16.17

PANEL B: SECOND STAGE RESULTS			
	Dependent variables:		
	Tot cites (log) (I)	Dirty cites (log) (II)	Tech distance (III)
GBAORD (log)	0.058*** (0.014)	0.049*** (0.0081)	0.005*** (0.00025)
Post Chernobyl	0.142*** (0.030)	0.061*** (0.022)	0.002*** (0.00075)
BERD (log)	-0.066** (0.026)	-0.045** (0.019)	-0.002*** (0.00074)
Emission intensity	-0.033* (0.018)	-0.003 (0.013)	-0.001** (0.00054)
Oil price (log)	0.063** (0.032)	0.000 (0.024)	-0.004*** (0.00083)
Patent FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	36,724	36,724	36,724

Notes: Panel A reports the first stage results. Panel B reports the second stage results. Columns I, II and III are based on the first stage reported in Panel A. All the models are estimated on the sample used in the main analysis, reduced by excluding patents invented in the US and in the UK. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$