Environmental policy and invention crowding out effect. Unlocking the automotive industry from fossil fuel path dependence.

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Background

Conceptual Framework

Data and Clustering

Empirical model

Results

The issue at stake

Mid 70s

Increased variety of low-emission vehicles (LEVs) that can compete with ICEVs, i.e. **electric** (EVs), **hybrid** (HVs) and **fuel cell** vehicles (FCVs). However...

- The market may select suboptimal technologies due to increasing returns to adoption (Arthur, 1989; Bruckner et al., 1996)
- Path-dependence in the type of innovation that is produced (Acemoglu et al., 2012)
- Uncertainty on what outcome of the innovation process will be selected (Nelson and Winter, 1982)
- Uncertainty on the capability of LEV to substitute ICEVs
- Uncertainty on the best alternative that should substitute ICEVs

Environmental policy (EP) and eco-innovation (EI)

Regulations may allow the automotive market escaping ICEVs lock-in (Cowan and Hultn, 1996)

Induced environmental innovation hypothesis (Popp et al. 2010)

- Increased knowledge spillover
- Reduces environmental externalities

Unintended effect related to EI and thus to EP (van den Bergh, 2013):

- Environmental rebound,
- Green paradox,
- Crowding-out

Crowding out (CO)

CO of other innovations

Eco-innovation may crowd out other (more) profitable innovations, at least when it is coupled with constrained financial resources to be devoted to R&D activities (Marin, 2014; Popp and Newell, 2012; Kneller and Manderson, 2012).

CO and EP

Other exceptions empirically investigate whether EPs are potential sources of crowding out (Hottenrott and Rexhuser, 2013; Gray and Shadbegian, 1998; Noailly and Smeets, 2015).

EPs bring to **higher opportunity costs** (financial and human real resources requirement) to develop EI needed to comply with EP requirements (Jaffe et al., 2002). **EPs are potential sources of crowding out, e.g. innovative efforts in environmental fields may drag away innovative efforts from non-environmental domains**

Research questions

Two main propositions (David, 1985; Arthur, 1989):

- Even if substituting technologies are available and superior to the dominant one, technological substitution is not warranted due to the presence of increasing returns to adoption
- When new technologies compete for the dominance, lock-ins into suboptimal alternative technologies are still possible due to path dependence of sequential adoption decision

Research questions:

- Does environmental policy induce a shift from non-environmental invention to environmental friendly inventive activities?
- Does environmental policy alter the competition among alternative low-emissions vehicles? Does it cause a shift among environmental inventive activities?

Data

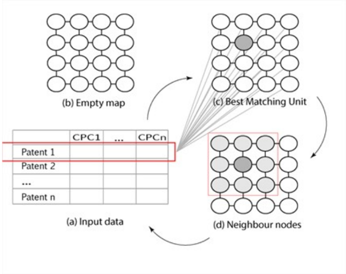
- 71 automotive firms included in the R&D scoreboards (IRI) from the 2006-2011 editions
- We used the Derwent Corporate Tree to retrieve their corporates' structure
- They have filed 247.510 patent families,
- of which 54.371 were triadic patent families (TPF)
- We used patent families earliest priority year (1978-2010)

We exploit CPC codes of each TPF to discern between what technologies compose the environmental and non-environmental technological domain

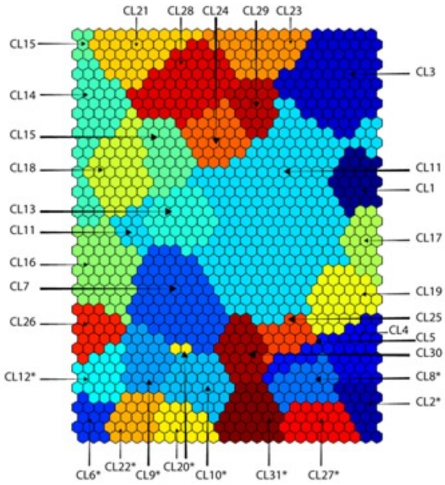
Clustering

Self-Organising Maps

- Unsupervised Artificial Neural Networks
- It identifies the similarities between multidimensional input data...representing them in a two-dimensional space
- It is a nonlinearity projecting mapping in which the input data become spatially and globally ordered (Kohonen, 2012)



Clustering results: Map



Clustering results: Table

Green patents: Y02 "Technologies or applications for mitigation or adaptation against climate change"

CL	Keywords	# of patents	% of green patents
1	Bore, crank, pistons	760	0
2	**Ignition, catalyst, throttle**	1455	**100**
3	Tyre, rubber, pneumatics	5328	1,33
4	Injector, spark, crank	1640	0
5	NOx, SOx, particulate	98	0
6	**Battery, hybrid, regeneration**	699	**99,86**
7	Cell, cathode, anode	1598	0,31
8	**NOx, catalyst, purification**	514	**98,25**
9	**Gear, stator, transmission**	174	**100**
10	**Spark, battery, octane**	347	**100**
11	Wiper, door, antenna	18568	0,15
12	**Transmission, gear, hybrid**	359	**99,44**
13	Stator, pole, rotor	882	0,68
14	Transmission, pulley, hydraulic	2864	1,26
15	Caliper, friction, brake	1330	0,9
16	Pointer, drowsiness, menu	1091	0
17	Injector, nozzle, carburetor	1673	7,23
18	Rubber, etch, windscreen	1076	0,37
19	Camshaft, rocker, crankcase	1445	0,14
20	**Hydrogen, electrolyte, cell**	525	**100**
21	Brake, master, skid	2047	0,64
22	**Battery, charger, PLC**	502	**99,6**
23	Airbag, inflate, retractor	2841	0,32
24	Suspensions, strut, axle	1001	0
25	Muffler, catalyst, silencer	357	0
26	Cruise, yaw, headway	604	0
27	Turbocharger, supercharger, swirl	1115	**100**
28	Robot, crawler, roof	1758	0,23
29	Rubber, flywheel, diaphragm	571	0
30	Oxide, palladium, acid	328	0
31	**Catalyst, NOx, purification**	820	**100**
	Total	54370	12,52

Dependent variable

Green Vs. non-Green hypothesis

$CO_{i,t} = (MA_{g,t} - MA_{g,t-1}) - (MA_{ng,t} - MA_{ng,t-1})$

Green Vs. Green hypothesis

$CO_{i,t} = |(MA_{g_1,t} - MA_{g_1,t-1}) - (MA_{g_2,t} - MA_{g_2,t-1})|$

Variables:

- i : each couple of g and ng clusters
- g : environmental cluster
- ng : non-environmental cluster
- MA : cluster patent count moving average

Empirical model

$$CO_{i,t} = f\left(\alpha_i, \gamma_{i,t}, EP_{i,t}, PROX_{i,t}, C_{g,ng,i,t}\right)$$

Variables:

- $EP_{g,ng,t} = \sum \left(w_{g,ng,c} * TIFP_{t,c}\right)$
- *TIFP*: tax-inclusive fuel prices
- α : cluster pairwise fixed effects
- γ: cluster pairwise time trends

Other variables:

- Number of citations between two clusters
- Own stock of patent for each cluster
- Number of firms that patent across two clusters

Main results

Table : Main results - Fixed-effects linear model

	(1) Gr vs. Non-Gr	(2) Gr. vs. Gr.
EP (t-1)	3.1682***	0.6117**
	(0.5538)	(0.2859)
PROX (t-1)	-0.2224***	0.0008
	(0.0126)	(0.0028)
CIT (t-1)	-0.1062*	-0.0266**
	(0.0627)	(0.0108)
NoF (t-1)	0.0189	-0.0010
	(0.0978)	(0.0652)
PS g (t-1)[a]	0.0924***	0.0162***
	(0.0039)	(0.0038)
PS ng (t-1)	-0.0091*	0.0175***
	(0.0046)	(0.0032)
_cons	490.1122	312.9676
	(512.3644)	(326.4627)
N	5670	2430
r2	0.4450	0.4485
F	9.0944	11.6531

The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: *CO* using 4-years moving average.
[a] In the first column the patent stock is calculated on green and non-green clusters. In the second column, even if we maintained same variable names, the clusters are both green.
Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Main results

Table : Model results using a different policy variable

	(3) Gr vs. Non Gr	(4) Gr. vs. Gr
EP_all (t-1)	3.2838***	0.6573**
	(0.5533)	(0.2817)
PROX (t-1)	-0.2224***	0.0008
	(0.0126)	(0.0028)
CIT (t-1)	-0.1053*	-0.0264**
	(0.0627)	(0.0108)
NoF (t-1)	0.0223	0.0008
	(0.0977)	(0.0651)
PS g (t-1)	0.0924***	0.0160***
	(0.0039)	(0.0038)
PS ng (t-1)	-0.0101**	0.0174***
	(0.0047)	(0.0032)
_cons	473.3723	311.8109
	(511.7267)	(326.1725)
N	5670	2430
r2	0.4452	0.4486
F	9.0745	11.6255

The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 4-years moving average. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table : Main results of fixed-effects linear model using fuel taxes as policy variable (1986-2008)

	(5) Gr vs. non-Gr		(6) Gr vs. Gr	
EP (t-1)	3.0881***		2.7583***	
	(0.8834)		(0.5844)	
ET (t-1)		11.9629**		12.0665***
		(5.3684)		-35.284
PROX (t-1)	-0.2309***	-0.2315***	0.0008	-0.0007
	(0.0132)	(0.0133)	(0.0033)	(0.0032)
CIT (t-1)	-0.1197*	-0.1267*	-0.0249**	-0.0279**
	(0.0649)	(0.0650)	(0.0108)	(0.0109)
NoF (t-1)	0.0389	-0.0025	0.0125	-0.0122
	(0.1017)	(0.1012)	(0.0688)	(0.0690)
PS g (t-1)	0.1071***	0.1084***	0.0065	0.0168***
	(0.0040)	(0.0041)	(0.0052)	(0.0044)
PS ng (t-1)	-0.0201***	-0.0030	0.0082*	0.0175***
	(0.0074)	(0.0055)	(0.0043)	(0.0037)
_cons	406.5658	1294.4763*	-85.1920	724.8870
	(656.7143)	(731.0743)	(433.4057)	(483.1778)
N	4830	4830	2070	2070
r2	0.4970	0.4960	0.4431	0.4399
F	8.2160	8.1272	9.2941	94.890

The two columns refer to the hypotheses tested above. Gr vs. non-Gr tests the dynamics of research efforts between green and non-green, whereas Gr vs. Gr tests the hypothesis that green research efforts drive away other green research efforts. Dependent variable: 4-years moving average. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Thanks

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Table : Correlation between percentage of patents per year in each environmental inventive activity.

Correlation matrix 1986-1993				
	End-of-pipe	EV	HV	FCV
End-of-pipe	1.00			
EV	-0.92	1.00		
	(0.00)			
HV	-0.01	-0.35	1.00	
	(0.99)	(0.39)		
FCV	-0.25	0.08	0.04	1.00
	(0.54)	(0.86)	(0.93)	
Correlation matrix 1994-2001				
End-of-pipe	1.00			
EV	-0.02	1.00		
	(0.97)			
HV	-0.79	-0.42	1.00	
	(0.02)	(0.30)		
FCV	-0.63	-0.53	0.51	1.00
	(0.09)	(0.18)	(0.20)	
Correlation matrix 2002-2009				
End-of-pipe	1.00			
EV	-0.71	1.00		
	(0.05)			
HV	-0.36	-0.31	1.00	
	(0.39)	(0.45)		
FCV	-0.70	0.20	0.30	1.00
	(0.05)	(0.64)	(0.48)	