Carbon Taxes, Path Dependency and Directed Technical Change : Evidence from the Auto Industry

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Introduction (1)

- Increased awareness about the importance of innovation and technological progress in fighting climate change and its consequences
- In a previous work, Acemoglu, Aghion, Bursztyn and Hemous (AABH, 2010) argued that factoring in endogenous directed technical progress changes our view of what the optimal environmental policy should look like
  1. it makes us reassess the costs of delayed intervention
  2. it leads to different policy prescriptions, e.g on the optimal mix of instruments

Introduction (2)

- A main ingredient in AABH is the assumption that there is *path-dependence* in the direction of technical change
  $\rightarrow$ namely, firms that have innovated a lot in dirty technologies in the past will find it more profitable to innovate in dirty technologies today

Introduction (3)

- This path-dependence assumption has four main implications:
  1. Because firms have innovated "dirty" in the past, they will continue to do so in the future
     $\rightarrow$ this in turn, under laissez-faire, may precipitate the occurrence of an environmental disaster
  2. The government can improve welfare and avoid a disaster by "redirecting" technical change.
  3. Delaying intervention is costly as firms will then continue to innovate dirty under laissez-faire, which in turn will increase the intervention cost tomorrow
  4. Temporary intervention may be sufficient: once firms have made enough clean innovations, path-dependence will play virtuously and ensure that even when left on their own firms will keep on innovating clean

Introduction (4)

- However, one might challenge the path-dependence hypothesis and wonder whether instead there should not be decreasing returns to each type (clean or dirty) of innovation
  $\rightarrow$ thus a firm that has innovated dirty a lot in the past would have more incentives to innovate clean today.
  $\rightarrow$ in that case the market should do at least part of the job of redirecting technical change towards clean technologies
- Whether this hypothesis is supported by empirical evidence is an open question

This paper (1)

- In this paper, we exploit a new patent data set on innovations in the car industry to show that:
  1. Higher fuel prices (and therefore higher carbon taxes) tend to redirect innovation towards clean technologies;
  2. Firms' propensity to innovate "clean" rather than dirty:
     $\rightarrow$ is positively correlated to the stock of past clean innovations
     $\rightarrow$ but is negatively correlated to the stock of dirty innovations
     - thereby vindicating the path-dependence hypothesis underlying the analysis in AABH
  3. the impact of a higher fuel price on the propensity to innovate clean is stronger for firms with a higher stock of *dirty* patents

This paper (2)

- We use patents filed at the European Patent Office between 1978 and 2007 to measure innovation in clean vs dirty transport technologies $\rightarrow$ our data include 12,000 patents in "clean" technologies (electric vehicles, hybrid vehicles, fuel cells,..) and 36,000 patents in "dirty" technologies which affect regular combustion engines.
- In our baseline empirical exercise we regress the ratio between the current flows of clean versus dirty patents on:
    1. the tax-adjusted price of fuel faced by consumers
    2. the firm's stocks of (past) clean and dirty patents
    3. interaction terms between the fuel price and patent stock variables
- Our regressions control for country-by-year and firms fixed effects.

Relation with literature

- The paper relates to a handful of empirical papers on the effect of energy prices on the direction of technical progress.
- In particular Popp (2002) uses U.S. patent data from 1970 to 1994 to study the effect of energy prices on energy-efficient innovations. $\rightarrow$ however, Popp does not look at the effect of past clean versus dirty innovations on current innovation, and in particular does not analyze whether there is path-dependence in the direction of technical change.
- Our paper is the first to jointly analyze the effect of energy price and of path-dependence on innovation at the firm level

Model (1): consumer and demand side

- One-period model of an industry populated by a mass 1 of different varieties.
- Demand structure for varieties is generated by the quasi-linear utility function

$$u = C_0 + \frac{\beta}{\beta - 1}\left(\int_0^1 c_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}\frac{\beta-1}{\beta}},$$

$\rightarrow$ where C_0 is a homogenous good and β is the elasticity of consumption of the composite good

- Then monopolist producing variety i will face inverse demand curve:

$$y_i = \left(p_i'\right)^{-\sigma} P^{\sigma-\beta} \qquad (1)$$

$\rightarrow$ where $\sigma > 1$ is the elasticity of substitution between the different varieties, ${p_i}'$ is the consumer (after tax) price, and P is the aggregate price index

$$P \equiv \left(\int_0^1 \left(p_i'\right)^{1-\sigma} di\right)^{\frac{1}{1-\sigma}}.$$

Model (2): production side

- Let x_{ji} denote the amount of clean ($j = c$) or dirty ($j = d$) energy inputs used by the producer of variety i, and let A_{ji} (with $j = c, d$) denote the productivity level for input j used by firm i.
- Variety i is produced according to:

$$y_i = A_{ci} x_{ci} + A_{di} x_{di}. \tag{2}$$

- Dirty energy pollutes: using x_{di} units of dirty energy input generates ξx_{di} ($\xi > 0$) units of atmospheric emissions.

Model (3): innovation

- Before production occurs a firm has the opportunity to innovate in clean and/or dirty technologies.
  $\rightarrow$ by hiring z_{ji} workers in R&D the producer can increase his productivity with input j from initial level A_{ji}^0 to

$$A_{ji} = (1 + \eta_j z_{ji})\, A_{ji}^0.$$

Model (4): government policy

- At the beginning of the period, the government can implement two types of environmental policies:
  1. a subsidy to research in the clean sector q
  2. a tax τ per unit of pollution.
- The relationship between the consumer and the producer (p_i) prices, is then given by

$$p_i' = p_i + \tau \frac{\xi x_{di}}{y_i}. \tag{3}$$

Model (5): timing of moves

- The timing of moves within the period can be summarized as follows:
  1. First, the government decides about research subsidies and pollution tax
  2. Then, producers decide how much to invest in clean and/or dirty innovation
  3. Then, production takes place

Equilibrium profits (1)

- The producer chooses the amount of energy inputs in order to maximize his profits

$$\Pi = P^{\frac{\sigma-\beta}{\sigma}} \left(A_c x_c + A_d x_d\right)^{\frac{\sigma-1}{\sigma}} - x_c - \left(1 + \tau\xi\right) x_d.$$

- Because the clean and dirty energy inputs are perfect substitutes, the producer uses the clean energy input only iff

$$A_c > \frac{A_d}{1+\tau\xi}.$$

Equilibrium profits (2)

- Equilibrium profits are then given by

$$\begin{aligned}\Pi_c &= P^{\sigma-\beta}\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}A_c^{\sigma-1} \text{ if } A_c > \frac{A_d}{1+\tau\xi}, \\ \Pi_d &= P^{\sigma-\beta}\frac{(\sigma-1)^{\sigma-1}}{\sigma^\sigma}\left(\frac{A_d}{1+\tau\xi}\right)^{\sigma-1} \text{ if } A_c < \frac{A_d}{1+\tau\xi}.\end{aligned} \tag{4}$$

where we recall that

$$A_{ji} = (1+\eta_j z_{ji})\,A_{ji}^0.$$

Innovation decision (1)

- Moving back one step, the producer chooses to invest in R&D labor to increase the productivity of the energy input she expects to use
  - If it turns out that it is more profitable to innovate and then produce clean, then the producer will invest in clean innovation with

$$\frac{(\sigma-1)^{\sigma}}{\sigma^{\sigma}} P^{\sigma-\beta} \left(A_c^0\right)^{\sigma-1} \eta_c \left(1+\eta_c z_c\right)^{\sigma-2} = 1-q; \tag{5}$$

  - If it turns out that it is more profitable to innovate and then produce dirty, then the producer will invest in dirty innovation with

$$\frac{(\sigma-1)^{\sigma}}{\sigma^{\sigma}} P^{\sigma-\beta} \left(\frac{A_d^0}{1+\tau\xi}\right)^{\sigma-1} \eta_d \left(1+\eta_d z_d\right)^{\sigma-2} = 1. \tag{6}$$

  - clean R&D investment z_c is increasing in the clean research subsidy q, and in the initial clean productivity A_c^0,
  - dirty R&D investment z_d is decreasing in the rate of pollution tax τ but increasing in the initial dirty productivity A_d^0.

Innovation decision (2)

- Now, one can show that firms will innovate clean whenever

$$\frac{A_c^0}{A_d^0} > \frac{\eta_d}{\eta_c}\frac{(1-q)}{(1+\tau\xi)}. \tag{7}$$

- In particular:
  1. producers are more likely to innovate (and then produce) clean when $\eta_c >> \eta_d$ or the larger q and/or the larger τ, or the larger the initial productivity ratio A_c^0/A_d^0.
  2. starting from a situation where (7) is violated, a *small increase* in q or τ may have no effect on clean innovation since that condition will remain violated so that producers will keep innovating dirty; yet, the increase in τ will reduce the amount of dirty innovation z_d - ignoring the general equilibrium effect going through the price index P
  3. a sufficiently *large increase* in q or τ will make (7) become satisfied, so that all R&D investment will go into clean.

Summarizing our main predictions

1. Producers have a higher propensity to innovate clean the larger q and/or the larger τ
2. Producers have a higher propensity to innovate clean the higher the initial productivity ratio A_c^0/A_d^0., i.e. the higher the stock of clean vs. dirty innovations
3. A small increase in q or τ will reduce the amount of dirty innovation but will have little or no effect on clean innovation
4. A sufficiently large increase in q or τ will push all R&D investment into clean.

Econometric specification (1):

- Our simplest dependent variable is the firm's propensity to currently innovate clean rather than dirty, which we capture by

$$RPAT_{it} = \ln(1 + PATC_{it}) - \ln(1 + PATD_{it})$$

  - where $PATC_{it}$ and $PATD_{it}$ are the flows of clean and dirty patents filed by firm i in year t.

- Explanatory variables:
  - A measure of government policy, G_{it}. We use tax-adjusted fuel price and fuel taxes.
  - The firm i's lagged clean and dirty patent stocks; i.e. $KPATC_{it-1}$ and $KPATD_{it-1}$.
  - The interaction between G_{it} and the stocks of clean and dirty patents.
  - Control variables: GDP, GDP per capita, firm fixed effects η_i, country fixed effects, year dummies

Econometric specification (2):

Thus we run:

$$\begin{aligned} RPAT_{it} &= \beta G_{it-k} + \alpha_1 KPATC_{it-1} + \alpha_2 KPATD_{it-1} \\ &\quad + \gamma_1 (KPATC_{it-1} * G_{it-k}) + \gamma_2 (KPATD_{it-1} * G_{it-k}) \\ &\quad + \Omega . X_{it} + \eta_i + u_{it} \end{aligned}$$

- We lag the policy variable by k periods as we expect the impact on patenting is not contemporaneous (baseline: k =1)
- We expect $\alpha_1 > 0, \alpha_2 < 0, \beta > 0$, $\gamma_1 < 0$, and $\gamma_2 > 0$.

Econometric specification (3):

We also estimate Poisson models of the form:

$$\begin{aligned} PATC_{it} &= \exp(\beta^C G_{it-k} + \alpha_1^C KPATC_{it-1} + \alpha_2^C KPATD_{it-1} \\ &+ \gamma_1^C (KPATC_{it-1} * G_{it-k}) + \gamma_2^C (KPATD_{it-1} * G_{it-k}) \\ &+ \Omega^C . X_{it} + \eta_i^C + u_{it}^C) \end{aligned}$$

and

$$\begin{aligned} PATD_{it} &= \exp(\beta^D G_{it-k} + \alpha_1^D KPATC_{it-1} + \alpha_2^D KPATD_{it-1} \\ &+ \gamma_1^D (KPATC_{it-1} * G_{it-k}) + \gamma_2^D (KPATD_{it-1} * G_{it-k}) \\ &+ \Omega^D . X_{it} + \eta_i^D + u_{it}^D) \end{aligned}$$

Data sources

- Our data comes from the World Patent Statistical Database (PATSTAT), maintained by the European Patent Office (EPO)
- We have extracted all the patents filed from 1978 to 2007 at the EPO pertaining to “clean” (C) and “dirty” (D) technologies in the automotive industry.
  $\rightarrow$ 37,103 patents in “dirty” technologies (related to regular combustion engine).
  $\rightarrow$ 12,438 patents in “clean” technologies (electric vehicles, hybrid vehicles, fuel cells,..).
- Fuel prices are from the IEA

Identifying companies' patent portfolios

- The PATSTAT database reports the name of patent applicants
  $\rightarrow$ to uniquely identify patent holders we rely on the OECD HAN database, which provides a dictionary of "cleaner" patent applicants' names produced through a computer algorithm.
  $\rightarrow$ as a result, we are able to match clean and dirty patents with 6827 distinct patent holders, 4366 of which are companies and 2461 are individuals.
- For every patent holder we subsequently identify the number of clean and dirty patent applications filed every year.

Patents as an indicator of innovation

- Main advantage: available at a highly disaggregated level and for all companies
    - Much better than R&D expenditures
- Limitations
    - Not all inventions are patented
      $\rightarrow$ Focusing on a single sector mitigates the problem
    - The value of individual patents is heterogeneous
      $\rightarrow$ We focus on patents filed at the EPO, which provides a quality threshold
      $\rightarrow$ We use citation data
    - The number of patents granted for a given innovation varies significantly across patent offices:
      $\rightarrow$ Using EPO patents to measure innovation provides a common measure

Constructing tax-adjusted fuel prices

- Data on fuel prices are only available at the country level
- Global firms may be influenced by variations in prices in different countries
- We construct a firm-level fuel price variable for each firm as a weighted average of fuel prices across countries where the firm sells
  - The weight of each country is determined by the importance of that country as a market outlet for that particular firm
  - To measure the exposure of a company to a specific market we use information on its patent portfolio
  - To make sure that the exposures are exogenous, the weights are calculated using the 1978-1985 "pre-sample" period and we estimate the regressions in 1986-2007
  - Moreover we use the complete firms' portfolio (in all technologies, no only clean and dirty)

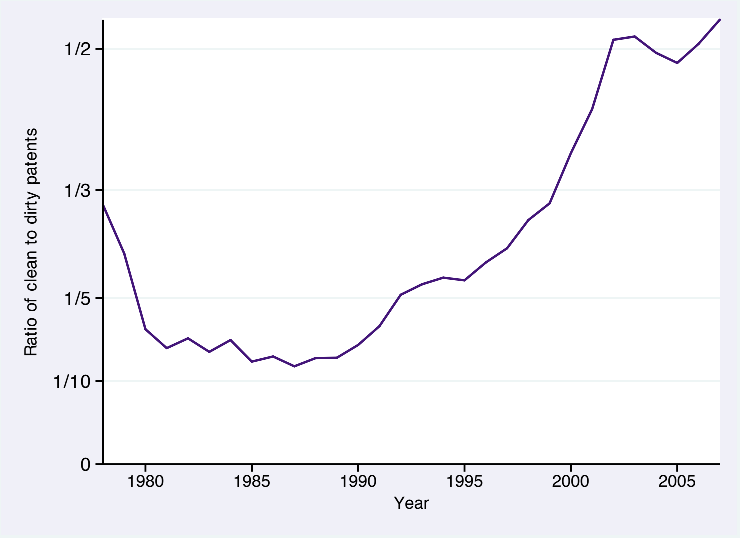
Example

- For example, suppose that a firm i has 3 patents over the period 1978-1985 (in clean, dirty, and other technologies)
- Out of these patents, 2 are patented in Germany and 1 in the US
- The firm is mostly present in Germany, but the German market is smaller than that of the US
- Each country receives a weight according to its 1978-1985 share in the world's GDP
- The price variable in our regressions would become

$$G_{it} = G_{Germany,t}. * s_{Germany} * (2/3) + G_{USA,t}. * s_{USA} * (1/3)$$

Descriptive statistics (1)

Ratio of clean to dirty patents filed at the EPO, 1978-2007



Descriptive statistics (2)

Geographical coverage of patent protection

Type of technology	Share of inventions also patented in:			
	USA	Japan	USA & Japan	China
Clean	75%	66%	59%	31%
Dirty	66%	59%	50%	17%

Descriptive statistics (3)

Knowledge spillovers:

		Cited patent		
		Clean	Dirty	Other
	Clean	55.2%	3.7%	40.1%
Citing patent	Dirty	1.0%	67.7%	31.3%
	Other	0.3%	1.2%	98.5%

Results

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications $\ln(1+Pc)-\ln(1+Pd)$				
Fuel Price (including tax)	1.688***		1.235***	0.838***	0.498**
$\ln P_{it-1}$	(0.246)		(0.225)	(0.201)	(0.194)
Stock of clean patents		0.161***	0.159***	0.158***	0.144***
$\ln(1+KPATC_{it-1})$		(0.014)	(0.014)	(0.014)	(0.015)
Stock of dirty patents		-0.085***	-0.084***	-0.080***	-0.046**
$\ln(1+KPATD_{it-1})$		(0.013)	(0.013)	(0.014)	(0.019)
Stock of clean patents X Fuel Price					-0.029
$\ln(1+KPATC_{it-1}) \times \ln P_{it-1}$					(0.046)
Stock of dirty patents X Fuel Price					0.131***
$\ln(1+KPATD_{it-1}) \times \ln P_{it-1}$					(0.032)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422

Separate regressions on clean and dirty

Dep.Variable	Number of Patent Applications					
	Clean			Dirty		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Fuel Price (including tax)	0.564***	0.307***	-0.006	-0.671***	-0.531***	-0.504***
$\ln(P_{it-1})$	(0.068)	(0.077)	(0.078)	(0.086)	(0.097)	(0.098)
Stock of clean patents	0.216***	0.216***	0.201***	0.057***	0.057***	0.057***
$\ln(1+KPATC_{it-1})$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Stock of dirty patents	0.036***	0.039***	0.072***	0.120***	0.120***	0.118***
$\ln(1+KPATD_{it-1})$	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Stock of clean patents X Fuel Price			-0.040***			-0.011
$\ln(1+KPATC_{it-1})$ X $\ln(P_{it-1})$			(0.006)			(0.007)
Stock of dirty patents X Fuel Price			0.125***			-0.006
$\ln(1+KPATD_{it-1})$ X $\ln(P_{it-1})$			(0.004)			(0.005)
Controls for GDP & Population	no	yes	yes	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes	yes
Year Controls	yes	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422	6422

Regressions with count data models

Dep.Variable	Patent counts			
	Clean	Dirty	Clean	Dirty
	(1)	**(2)**	**(3)**	**(4)**
Fuel Price (including tax)	1.239***	-0.828***	1.360***	-0.329***
$\ln(P_{it-1})$	(0.139)	(0.089)	(0.140)	(0.086)
Stock of clean patents	1.456***	-0.102***	1.462***	-0.070***
$\ln(1+KPATC_{it-1})$	(0.008)	(0.006)	(0.008)	(0.006)
Stock of dirty patents	-0.010*	1.352***	-0.020**	1.431***
$\ln(1+KPATD_{it-1})$	(0.006)	(0.004)	(0.009)	(0.005)
Firm Fixed Effects	no	no	yes	yes
Year Controls	yes	yes	yes	yes
Observations	141284	141284	141284	141284
Firms	6422	6422	6422	6422

A stronger response to large price increases?

	(1)	(2)	(3)
Dep. Variable	Ratio between Clean and Dirty Patent applications		
Fuel Price (including tax)	1.278***	0.684**	0.083
$\ln P_{it-1}$	(0.232)	(0.298)	(0.277)
Fuel Price squared	0.222***	-0.102	-0.211
$(\ln P_{it-1})^2$	(0.070)	(0.142)	(0.132)
Stock of clean patents	0.159***	0.158***	0.150***
$\ln(1+KPATC_{it-1})$	(0.014)	(0.014)	(0.016)
Stock of dirty patents	-0.080***	-0.081***	-0.048**
$\ln(1+KPATD_{it-1})$	(0.014)	(0.014)	(0.020)
Stock of clean patents X Fuel Price			-0.180**
$\ln(1+KPATC_{it-1}) \times \ln P_{it-1}$			(0.072)
Stock of dirty patents X Fuel Price			0.191***
$\ln(1+KPATD_{it-1}) \times \ln P_{it-1}$			(0.053)
Stock of clean patents X Fuel Price^2			-0.394***
$\ln(1+KPATC_{it-1}) \times (\ln P_{it-1})^2$			(0.153)
Stock of dirty patents X Fuel Price^2			0.118
$\ln(1+KPATD_{it-1}) \times (\ln P_{it-1})^2$			(0.092)
Controls for population & GDP	no	yes	yes
Firm Fixed Effects	yes	yes	yes
Year Fixed Effects	yes	yes	yes
Observations	141284	141284	141284
Firms	6422	6422	6422

Robustness check: 2 years lag of fuel price

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications ln(1+Pc)-ln(1+Pd)				
Fuel Price (including tax)	1.932***		1.400***	0.883***	0.459**
$\ln P_{it-2}$	(0.281)		(0.260)	(0.217)	(0.201)
Stock of clean patents		0.161***	0.159***	0.159***	0.142***
$\ln(1+KPATC_{it-1})$		(0.014)	(0.014)	(0.014)	(0.016)
Stock of dirty patents		-0.085***	-0.083***	-0.080***	-0.037*
$\ln(1+KPATD_{it-1})$		(0.013)	(0.013)	(0.014)	(0.021)
Stock of clean patents X Fuel Price					-0.032
$\ln(1+KPATC_{it-1})$ X $\ln P_{it-2}$					(0.049)
Stock of dirty patents X Fuel Price					0.143***
$\ln(1+KPATD_{it-1})$ X $\ln P_{it-2}$					(0.035)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422

Robustness check: Fuel tax instead of fuel price

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications ln(1+Pc)-ln(1+Pd)				
Fuel tax	1.643***		1.116***	0.616**	0.26
ln P_{it-1}	(0.308)		(0.287)	(0.312)	(0.294)
Stock of clean patents		0.161***	0.159***	0.159***	0.218***
ln(1+$KPATC_{it-1}$)		(0.014)	(0.014)	(0.014)	(0.053)
Stock of dirty patents		-0.085***	-0.083***	-0.080***	0.02
ln(1+$KPATD_{it-1}$)		(0.013)	(0.013)	(0.014)	(0.044)
Stock of clean patents X Fuel Tax					0.09
ln(1+$KPATC_{it-1}$) X ln P_{it-1}					(0.064)
Stock of dirty patents X Fuel Tax					0.113***
ln(1+$KPATD_{it-1}$) X ln P_{it-1}					(0.041)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422

Robustness check: Companies only

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications ln(1+Pc)-ln(1+Pd)				
Fuel Price (including tax)	2.016***		1.479***	0.993***	0.580**
ln P_{it-1}	(0.314)		(0.284)	(0.265)	(0.255)
Stock of clean patents		0.174***	0.172***	0.172***	0.154***
ln(1+$KPATC_{it-1}$)		(0.014)	(0.014)	(0.014)	(0.016)
Stock of dirty patents		-0.120***	-0.119***	-0.115***	-0.078***
ln(1+$KPATD_{it-1}$)		(0.015)	(0.015)	(0.016)	(0.020)
Stock of clean patents X Fuel Price					-0.050
ln(1+$KPATC_{it-1}$) X ln P_{it-1}					(0.048)
Stock of dirty patents X Fuel Price					0.156***
ln(1+$KPATD_{it-1}$) X ln P_{it-1}					(0.033)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	91982	91982	91982	91982	91982
Firms	4181	4181	4181	4181	4181

Robustness check: alternative definition of clean

We consider that fuel reduction patents are "clean" (8,000 patents)

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications ln(1+Pc)-ln(1+Pd)				
Fuel Price (including tax)	1.334***		1.072***	0.755***	0.609***
$\ln P_{it-1}$	(0.213)		(0.197)	(0.181)	(0.171)
Stock of clean patents		0.126***	0.124***	0.124***	0.121***
$\ln(1+KPATC_{it-1})$		(0.012)	(0.012)	(0.012)	(0.014)
Stock of dirty patents		-0.049***	-0.047***	-0.045***	-0.031**
$\ln(1+KPATD_{it-1})$		(0.010)	(0.010)	(0.010)	(0.015)
Stock of clean patents X Fuel Price					0.005
$\ln(1+KPATC_{it-1}) \times \ln P_{it-1}$					(0.038)
Stock of dirty patents X Fuel Price					0.052*
$\ln(1+KPATD_{it-1}) \times \ln P_{it-1}$					(0.029)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422

Regressions with country specific time effects

	(1)	(2)	(3)	(4)	(5)
Dep. Variable	Difference between Clean and Dirty Patent applications ln(1+Pc)-ln(1+Pd)				
Fuel Price (including tax)	1.782***		1.351***	0.958***	0.616***
$\ln P_{it-1}$	(0.250)		(0.229)	(0.204)	(0.199)
Stock of clean patents		0.159***	0.157***	0.156***	0.142***
$\ln(1+KPATC_{it-1})$		(0.014)	(0.014)	(0.014)	(0.015)
Stock of dirty patents		-0.086***	-0.084***	-0.081***	-0.047**
$\ln(1+KPATD_{it-1})$		(0.013)	(0.013)	(0.014)	(0.019)
Stock of clean patents X Fuel Price					-0.030
$\ln(1+KPATC_{it-1})$ X $\ln P_{it-1}$					(0.046)
Stock of dirty patents X Fuel Price					0.130***
$\ln(1+KPATD_{it-1})$ X $\ln P_{it-1}$					(0.032)
Controls for population & GDP	no	no	no	yes	yes
Firm Fixed Effects	yes	yes	yes	yes	yes
Country by Year Fixed Effects	yes	yes	yes	yes	yes
Observations	141284	141284	141284	141284	141284
Firms	6422	6422	6422	6422	6422

Summary of results

- Higher fuel price encourage innovation in clean technologies relative to innovation in dirty technologies
  $\Longrightarrow$ consistent with the directed technical change hypothesis
- Firms build on their existing stock of technology-specific knowledge to develop new innovation, which can lead to technological lock-in
  $\Longrightarrow$ consistent with the path-dependence hypothesis
- Firms that have already innovated clean in the past, react less to price effects
  $\Longrightarrow$ a fuel price increase has a small effect on firms already specialized in clean technologies

Robustness

- Our results are robust to:
    1. using the tax component of the fuel price instead of the fuel price
    2. using various lags of the price
    3. including other variables besides fuel price (GDP, GDP per capita) but weighted in the same way as fuel price
    4. including country-by-year fixed effects that control for technology-push policies
    5. using an alternative definition of clean patents
    6. using the level of clean patenting and the level of dirty patenting as two separate left hand side variables
    7. modifying the period used to calculate the weights
    8. dropping individual patent holders (1/3 of the data set)
    9. dropping the top 1% patent holders in terms of both, clean and dirty innovation

Policy implications

1. In addition to reducing consumer demand for carbon, higher carbon taxes induce relatively more clean innovation, which magnifies the benefit of such a policy
2. Absent government intervention, firms that have innovated dirty in the past tend to get locked in the same type of innovative activities in the future
   $\Longrightarrow$ This makes the task of climate change mitigation harder as the default option of the economy is to increase demand for carbon-using technologies
   $\Longrightarrow$ This calls for early action
3. Pollution taxes redirect innovation towards clean mostly where this is needed the most, namely in firms with higher stocks of past dirty innovations

Next steps

1. Test the other prediction of the model
$\rightarrow$ namely, that, unlike with the carbon tax, clean research subsidies should boost clean innovation *more* in firms with bigger stock of clean innovations
2. Use microeconomic data to estimate other parameters of importance in AABH:
    - elasticity of substitution between clean and dirty inputs
    - productivity of innovation and imitation in clean and dirty technologies
3. Implementability of carbon tax versus research subsidies