Does environmental regulation drive specialisation in green innovation?*

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Abstract

We examine the response of technological change to one of the major environmental regulations in the European Union (EU) – the Ambient Air Quality Directive (AAQD). Our identification strategy exploits the structure of this directive, which imposes air quality measures in regions exceeding pollutant concentration limits. We implement a quasi difference-in-differences strategy and test for the effect of environmental measures on innovation in 654 technology classes at the EU region (NUTS-2) level over the 1999-2015 period. We show that AAQD environmental measures drive the specialisation of regions in green technologies. We find a positive effect for patents in the two most prevailing green technology classes, i.e., clean energy and industrial processes, as well as evidence of spatial leakage.

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1 Introduction

In many countries, policy efforts have been undertaken to improve air quality. National Ambient Air Quality Standards (AAQS) that limit local air pollutant concentrations have been implemented in 109 out of 194 countries, and most developed and emerging economies have established binding rules and regulations to commit to these standards (UNEP, 2016).[1] These regulations are all the more necessary given the multiple consequences of air pollution. Apart from health effects, air pollution also negatively affects key ecosystems, like forests or freshwater, might exacerbate pandemics and contributes to accelerating climate change. It is now established that air pollution and climate change are closely interlinked (EEA, 2016). However, the ability of air pollution regulations to temper climate change and its associated costs largely depends on their impact on technological change.

Do air pollution regulations stimulate innovations that mitigate climate change? By imposing limits on polluting emissions or by increasing their costs, these measures should affect the direction of technological change (Acemoglu et al., 2012). Firms might respond to the regulation by investing in innovative technologies that reduce the cost of complying with the regulation (Brunnermeier and Cohen, 2003). However, redirecting technological change is not straightforward due to path dependence (Aghion et al., 2016) and because environmental regulation in one country could divert polluting activities toward less regulated countries via trade or investment flows (Bagayev and Lochard, 2017). The answer to this question is largely an empirical matter. In this paper, we provide the first comprehensive examination of the causal effect of air pollution regulation on specialisation in green innovations.

We implement a quasi difference-in-differences strategy to test for the impact of air pollution measures on innovation in 654 technology classes in 273 European Union (EU) NUTS-2 regions over the 1999-2015 period. We rely on the major EU air policy – the Ambient Air Quality Directive (AAQD). This directive sets numerical limits and thresholds for different

[1]The Clean Air Act since 1963 in the U.S., the Air Pollution Control Act since 1968 in Japan or the Law on Prevention and Control of Air Pollution (Air Law) since 1987 in China are a few examples around the world.

types of pollutants and requires countries to implement and enforce environmental measures at the local level in case of exceedance. Our identification strategy takes advantage of the design of this directive, which is applicable in the entire EU and provides an arguably exogenous environmental stringency change that varies on a region-year basis. As such, it offers a unique opportunity to consistently analyse the full policy impact of air pollution regulations on green innovations.

We find that air quality measures affect specialisation in green innovations within the EU. Our analysis yields three main insights. First, regions that implement additional environmental measures tend to innovate more in energy sources alternative to fossil fuels and in green technologies related to the production or processing of goods, representing approximately half of green innovations. The contemporaneous direct consequence of the regulation is an increase in patents of 6 to 13% in these two classes, while the cumulative effect occurring through a rise in the stock of green patents is between 12 and 26%. Second, the regulation has no impact on green innovations in transportation, the second largest class of green patents in Europe. Third, we find evidence of spatial leakage. Some environmental measures trigger specialisation in local green innovations but, at the same time, reduce them in proximate regions. Our results are supported by a placebo test based on the specific design of the regulation and are robust to confounding factors and to other sources of endogeneity.

This paper relates to the literature on directed technical change (e.g., Acemoglu, 2002, Acemoglu and Finkelstein, 2008), in particular on the forces shaping technical change towards greener innovations (Acemoglu et al., 2012, Acemoglu et al., 2016). As technology is path dependent, a crucial point in this literature is that policy intervention is necessary to achieve sustainability goals and to do so at a lower cost. A growing number of papers focus empirically on the role of carbon pricing in inducing clean innovation. An important part of this literature looks at the effect of energy prices on directing technological change towards specific innovations (Newell et al., 1999, Popp, 2002).[2] In particular, Aghion et al. (2016) analyse

[2]The early empirical literature investigates the link between environmental policies and technological change at the sector or country level (see Popp et al., 2010, for a review). One of the challenges encountered in this literature is, however, to determine the causal effect of environmental regulation. The presence of third

the auto industry and show that firms tend to innovate more in clean technologies, such as electric or hybrid vehicles, when tax-inclusive fuel prices are higher. Moreover, they depict a path dependence pattern: firms that used to innovate in clean (resp. dirty) technologies in the past will also tend to innovate in clean (dirty) technologies in the future. Another paper by Calel and Dechezleprêtre (2016) uses firm-level data to investigate the role of carbon pricing through the impact of the European Union Emissions Trading system (EU-ETS) on the number of low-carbon patents. Using quasi-experimental techniques, comparing regulated and comparable non-regulated firms before and after the launch of the EU-ETS in 2005, they show that the EU-ETS increases the number of low-carbon patents among regulated firms by less than 10% (183 additional patents). This explains just 1% of the overall increase in low-carbon patenting because regulated firms only account for a small share of all patents.[3] We contribute to these recent developments in the literature by providing empirical evidence on the causal effect of air pollution regulation in directing technical change. The AAQD is the largest and most important environmental legislation of its kind in the EU, which would, as such, make it a compelling policy to study. However, more importantly, it allows analysing, at a granular regional level, the full spectrum of patented innovations in the entire EU to consistently isolate a sizeable impact of air quality regulation. The regional level is the appropriate unit of observation because most air quality measures are implemented at this level. Furthermore, there is ample evidence that innovative activity is highly localised and that knowledge spillovers are geographically bounded (e.g., Audretsch and Feldman, 2004).

We also add to the literature looking at the economic effects of air quality regulations. Potential consequences of these regulations have been investigated in several areas, including health, pollution, labour, economic activity, FDI and housing prices (see, for example, Green-

factors, including unobserved technology shocks, that influence both regulatory stringency and technological change and reverse causality running from innovations to environmental policies are potential sources of endogeneity.

[3]The firm-level analysis probably leads to an underestimation of the policy effect because firms that are not directly covered by the regulation might also be affected. In our research work, we identify the impact of environmental regulation at the regional level, which seems to be the most appropriate level of analysis (see below).

stone, 2002, Hanna, 2010, Walker, 2011, Greenstone and Hanna, 2014, Bento et al., 2015, Gibson, 2019, Anderson, 2020, or Currie and Walker, 2019 for a recent review).[4] However, relatively little is known about their impact on innovations. A few papers investigate trends in specific technologies after the implementation of air quality standards. In particular, the work by Popp (2006) uses patent data to analyse international flows of innovations between the United States, Japan, and Germany in pollution control technologies designed to reduce emissions of nitrogen oxide (NOx) or sulphur dioxide (SO2) from coal-fired power plants. His results suggest that inventors in these specific technologies respond to regulatory pressures in their own country, but not to foreign pressures. However, these findings might be biased by technology or macroeconomic confounding effects. Our paper complements this literature and provides evidence of a causal impact of air quality policy on the direction of technical change, which is not narrowed down to one specific policy instrument, technology or sector.

In the next section, we present our empirical strategy, identification and data. Then, in Section 3, we report our main results on the effect of environmental regulation on green innovations. In Section 4, we discuss endogeneity issues. Finally, in Section 5, we summarise our main findings.

2 Methodology and data

2.1 Empirical strategy

Our aim is to assess the effect of environmental measures on innovation at the regional level. Our identification relies on a quasi difference-in-differences setting including a wide range of fixed effects to control for omitted variables. This design allows us to evaluate whether patenting activity in green technologies is disproportionately more affected in regions enforcing additional air pollution regulations.

[4] Most of the papers in this literature analyse the impact of regulations induced by the U.S. Clean Air Act. One exception using the EU case studying the effect of the AAQD on redirecting pollution-intensive imports is Bagayev and Lochard (2017).

The basic Poisson specification is as follows:

$$
\begin{aligned}
Patents_{rct} &= exp(\alpha_1(1-\delta)K_{rct-1} + \alpha_2 RegAQ_{rt} \times Green_c \\
&+ \alpha_3 RegAQ_{rt} \times Comp_c + \gamma_{rc} + \gamma_{c1t} + \gamma_{rt}) + \epsilon_{rct}
\end{aligned} \tag{1}
$$

where $Patents_{rct}$ is the count of patents in EU region r applied for a given technology class c at the 4-digit level and year t.[5] $(1-\delta)K_{rct-1}$ is the region's knowledge capital as given by the stock of patents in the previous period depreciated by a rate δ.[6] $RegAQ_{rt}$ is the measure of a region's environmental regulation change due to the exceedance of a given pollutant concentration as imposed by the EU Ambient Air Quality Directive (see Section 2.2), and $Green_c$ is a dummy variable capturing the class of patents pertaining to the "technologies or applications for mitigation or adaptation against climate change", i.e., classes Y02 and Y04S in the Cooperative Patent Classification. In further refinements of our results, we study how regulations related to different pollutants affect different subclasses of green technologies (see Section 2.3 and Table A4 in the Appendix for further details). As technologies can be related to one another, we isolate the effect of environmental regulation on green innovations from its effect on other technology classes by controlling for technologies that are complementary to green classes. More precisely, we include an interaction term between the variable of environmental regulation and a dummy capturing whether a given non-green class is complementary to each Y02/Y04S class ($Comp_c$, see Section 2.3 for further details and the Appendix for the construction of this variable). γ_{rc} are technology class-region fixed effects, γ_{rt} are region-year fixed effects and γ_{c1t} are class (1 or 4-digit)-year fixed effects.[7]

[5] All variables and sources are defined in the Appendix (Table A1).

[6] Stocks are constructed using the perpetual inventory method with the knowledge depreciation rate set at 20% (e.g., Aghion et al., 2016). The value of a given patent is set to zero after 20 years. We use the inverse hyperbolic sine (IHS) transformation for the stock variable rather than the log transformation because it is defined for zero values; it is similar to a log and can be interpreted as percentage impacts, except for small values of the stock variable.

[7] The inclusion of the 4-digit class × year fixed effects (in addition to the 4-digit class × region and region × year fixed effects) for all technology classes is computationally burdensome because of the size of

All these fixed effects are crucial to control for regional specialisation in innovative activity, region-specific shocks, and technology trends and shocks common to all regions. Finally, ϵ_{rct} is the usual error term.

Equation (1) allows comparing specialisation in green (vs. non-green) innovations of regions that implement additional environmental measures and specialisation of similar regions that do not. The coefficient of interest, α_2, measures any difference between the two after controlling for all major innovation determinants at the regional level, which can therefore be attributed to environmental regulation. One important assumption underlying our identification strategy is that there are no other region-class time-varying factors correlated with the treatment that we consider (environmental measures). We further discuss this assumption and test the robustness of our results by estimating our model on different subsamples and by introducing additional control variables varying at the region-class-year (rct) level (see Section 3.2).

Because our dependent variable is a count of patents, we use a Poisson model and a high-dimensional fixed effects procedure extended to nonlinear models (see Guimaraes and Portugal, 2010). This procedure allows us to include up to 92,114 fixed effects on a sample of 1,198,944 observations.[8]

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the matrix to estimate and the loss of degrees of freedom. To overcome this problem, we incorporate in our estimations 4-digit class $\times$ year fixed effects for green technology classes only and 1-digit class $\times$ year fixed effects for other classes. This accounts for the fact that we can observe a general increasing trend for some green technologies (e.g., clean energy) and a negative trend for others (e.g., capture and storage of greenhouse gases), independent of whether the region has to implement environmental measures.

[8]In the original sample, approximately half of the region-technology class pairs and 5% of the region-year pairs have zero patents or are singletons. Singletons can be perfectly predicted in-sample with fixed effects and do not add any useful information for the estimates. On the other hand, they can bias the calculation of clustered standard errors and considerably slow down the computation of the maximum likelihood. Our estimation routine thus excludes singletons from the estimation, which explains why out of 3,035,214 ($= 654 \times 273 \times 17$) potential observations, our sample is composed of 1,198,944.

2.2 Environmental regulation measure

Our proxy variable for environmental regulation is based on the Ambient Air Quality Directive (2008/50/EC). The AAQD is the main regulation to fight air pollution in EU member states. It sets numerical limits and thresholds for the most prevalent air pollutants (see Table A2 in Appendix) and forces EU countries to implement environmental measures in case of exceedance.

The general principles of the regulation are as follows.[9] For the purposes of air quality assessment and monitoring, member states have to define geographical areas within their territories. These zones include all agglomerations with a minimum population of 250,000 inhabitants and generally correspond to administrative regions. Air pollution concentration is measured by more than 4,000 stations located in these regions and distributed across the EU. The AAQD then requires member states to draw up and report detailed plans and programs for zones in which at least one pollutant exceeds its limit value to fall below the limit value. These measures include medium- or long-term actions, such as the development and the adoption of environmentally friendly innovations, as well as short-run actions (e.g., suspensions or restrictions of polluting activities contributing to non-attainment, traffic restrictions). Firms might directly respond to the regulation by developing innovations that allow them to comply with air quality standard or to reduce the cost of the regulation. The link to innovation might also be more indirect if higher adoption of green innovations in regulated zones creates a demand-pull for green technologies and therefore fosters innovation. In this setting, we expect AAQD to more generally affect environmentally friendly innovations and not only innovations targeting one pollutant or another.

We focus here on compliance with limit values for two major pollutants, particulates (PM10) and nitrogen dioxide (NO2). They represent the target of most (68%) air quality plans implemented since 2004 (see also EEA, 2018) and are the most reported pollutants by monitoring stations (73% of all station-years over 1999-2015 for NO2 and 62% for PM10).

An important characteristic of the AAQD is that these limit values are legally binding,

[9] A detailed description of the regulation is provided in the Appendix.

meaning that judicial actions may be undertaken if a member state fails to comply with the regulation. For PM10 and NO2, eight countries have recently referred to the Court of Justice for systematic and continuous exceedance in several regions. As a robustness check, we exclude these regions from the sample, considering that they have not fully implemented environmental measures to comply with the regulation (see Section 3.2).

Finally, most environmental measures are decided and implemented at the regional level.[10] Among the 51,530 measures reported for the years 2012 to 2016, 89% are local or regional and 11% are national.[11] Therefore, in our empirical analysis, we consider the regional level to be the most appropriate because the environmental measures and constraints faced by firms are essentially perceived at this level.

We use exceedances of limit values for NO2 and PM10 pollutants as proxies for changes in environmental stringency. More precisely, we construct, for each NUTS-2 region and year, a dummy variable (RegAQ) that measures exceedances of air quality limit values for each pollutant after the entry into force of the regulation (2005 for PM10 and 2010 for NO2; limit values are displayed in Table A2 in Appendix). This variable does not evaluate the overall level of environmental policy stringency but rather *additional* environmental measures implemented by EU regions to comply with the AAQD. In our empirical estimations, we also use an alternative variable for RegAQ: the average exceedance level above the limit value (average number of days or times of exceedance by region and year) over the allowed level.[12] This variable intends to measure the magnitude of exceedances, which should correlate with the stringency of the regulation.

Figure A1 in the Appendix displays the average number of exceedances of limit values over

[10]Note, however, that each member state is responsible for implementing adequate measures in case of exceeding.

[11]Source: EEA, Air quality measures (data flow K).

[12]For example, the hourly limit value for NO2 is 200μg/m3 not to be exceeded more than 18 times a year (see Table A2 in Appendix). In 2010, six stations in the Madrid region in Spain exceeded the limit. The average number of times of exceedances for this region and year is 42.88, so that our RegAQ variable in this case is equal to 1.38 ($= (42.88 - 18)/18$).

allowed values by country and year for NO2 and PM10. It shows that over our period of time (1999-2015), several countries, including both old and more recent EU countries, have at least one exceedance above the limit value and therefore should have implemented additional environmental measures in at least one region to comply with the regulation. The number of exceedances over the allowance also decreases over time for the two pollutants.

Using exceedance of limit values as a proxy for environmental regulation has several advantages. It allows us to tackle two major problems, i.e., simultaneity and multidimensionality, that have been widely documented in the literature (e.g., Levinson and Taylor, 2008). First, the ambient air quality limits we consider are equally and uniformly imposed on all EU countries and are based on considerations related to the protection of human health. Thus, all member states face the same limit values, which are exogenous to their own economic activity or preferences (lobbying from citizens or industrial sectors). Second, environmental regulation is multidimensional, and regional or national authorities use many different instruments to achieve their objectives (Brunel and Levinson, 2013). Here, we do not focus on one particular measure, such as the lead content of gasoline or ecotaxation. Indeed, within the AAQD framework, regions have high flexibility in implementing adequate measures to reduce emissions below the limits imposed by the directives. On the downside, our proxy for environmental regulation does not allow us to compare the effects of different policy instruments on clean innovations (see, e.g., Veugelers, 2012).

Furthermore, the AAQD is relatively effective, and most regions and countries implement environmental measures in the case of exceedances. Finally, the AAQD is the most constraining legislation compared to other EU directives. The other major legislation dealing with air quality, the National Emission Ceilings Directive (NECD) adopted in 2001 sets emission ceilings specific to each member state for four pollutants (SO2, NOx, COV and NH3) that have to be met by 2010.[13] For the two pollutants that we consider here, only NOx appears in both directives. Moreover, most countries met their national emission ceilings for NOx during the 2010-2015 period. In robustness checks, we control for potential measures

[13] The revision of the NECD in 2016 adds a fifth pollutant (PM2.5) and sets new emission reduction commitments for 2020 and 2030.

unrelated to AAQD but related to NECD (see Section 3.2). Note that there are also specific emission standards coming from other directives (such as the Industrial Emissions Directive or the Medium Combustion Plant Directive), but they are source- or product-related and generally support the targets of the AAQD and NECD.

2.3 Patent data

Patent data have been used extensively as a measure of technological innovation. This measure has both pros and cons compared to alternative measures, such as R&D expenditures or R&D personnel (e.g., OECD, 2009; Dechezleprêtre et al., 2011). On the one hand, as a way of protecting inventions, patents are a natural measure of the output of the innovation process (Griliches, 1990). Moreover, they provide detailed information on the nature of the invention, its technological content, the inventors involved, including their geographical locations at the time of invention, and other useful indicators. On the other hand, patents capture only one way for firms, institutions or individuals to protect inventions. Patent values are also quite heterogeneous: some patents generate high economic rents while others might remain unexploited in the marketplace.

Following the recent literature, we proxy innovative change in a given technology class by the number of patents applied in that very class. For the purpose of our empirical strategy, we use patent data information at the EU NUTS-2 level broken down by technology class. These data come from the European Patent Office (EPO) Worldwide Patent Statistical Database (PATSTAT).[14] Patents were classified using the Cooperative Patent Classification (CPC) scheme. We use annual counts of patent applications to the EPO (whether granted or not) at the 4-digit technology class level based on the date of priority. We follow the literature and consider only EPO patents (and not patents exclusively filed with national patent offices) to ensure that the patents that we consider are of high quality (see, e.g., Calel and

[14] Similar data have been used, for example, by Kogler et al. (2017) to measure knowledge produced within each NUTS-2 region and thus map the knowledge space of the EU15 countries between 1981 and 2005.

Dechezleprêtre, 2016).[15]

We use information on the region of residence of the inventor(s) to capture the geographical distribution of patents. To avoid double counting, we follow common practice and use fractional counting. If a patent was developed by several inventors located in various EU NUTS-2 regions at the time of the invention, we equally divide the patent among all regions. In the final sample, we have patents in 654 CPC classes (4-digit level) for 273 regions in 28 EU countries over the 1999-2015 period.

To measure the direction of technological change and identify innovations that should foster climate change mitigation, we rely on the recently developed classes pertaining to "technologies or applications for mitigation or adaptation against climate change" (Veefkind et al., 2012). This new tagging scheme - encompassing the Y02 and Y04S classes - has been developed by means of search strategies by expert examiners and formalised into algorithms. Thus, it consistently applies to patents filed during our period of investigation (and before). The Y02 category now includes eight different subclasses and allows for a detailed analysis of the environmental measures that impact different types of Climate Change Mitigation Technologies (CCMTs). The eight subclasses are defined as follows: Y02A (Adaptation to climate change), Y02B (Buildings), Y02C (Capture and storage of greenhouse gases), Y02D (ICT aiming at the reduction of own energy use), Y02E (Production, distribution and transport of energy), Y02P (Production and processing of goods), Y02T (Transportation) and Y02W (Waste and wastewater) (see Table A4 in Appendix). The class Y04S relates to smart grids. In our empirical analysis, we have all the subclasses except Y02A and Y02D, which are too recent for our current dataset. Among the existing categorisations, the Y02/Y04S tagging scheme is the most comprehensive and accurate, and has been used in several recent papers focusing on clean innovations (e.g., Calel and Dechezleprêtre, 2016).[16]

[15] As argued by Calel and Dechezleprêtre (2016), only high-value inventions typically get patented at the EPO.

[16] The OECD proposes an alternative measure of environment-related technology classes (ENV-tech) based on the identification of relevant CPC patent classes (see Haščič and Migotto, 2015). However, this classification identifies classes and not patents, and these classes are compiled at different levels of aggregation.

Unlike other CPC classes, the Y02/Y04S scheme has been defined as a purely *complementary* tagging scheme (Veefkind, 2012). In that sense, it comes at the top of the existing CPC classification and does not replace any previously reported CPC class. Patents tagged with one of the green classes should thus, by construction, also be assigned to other regular (non-green) CPC classes. To consistently disentangle green patents from non-green patents, we adopt two strategies. First, any patent tagged with a green class is not reported in any other CPC class. Second, we account for the complementarity between green and non-green classes by introducing an additional dummy variable ($Comp_c$ in equation 1) capturing whether a given non-green class is *complementary* to each Y02/Y04S class using probabilistic cooccurrences between technology classes (see the Appendix for details). Not considering this complentarity between CPC classes could bias our coefficients downward, and the extent of the bias could be different across the Y02/Y04S classes.

To illustrate this, let us consider the example of a firm that develops and patents innovations related to CO2 capture in the face of new air pollution regulations. Technologies and innovations this firm would develop should thus be related to the Y02C class but also to the B01D class which, in short, relates to innovations in "separation of gases". Accordingly, everything else held constant, the increase in environmental regulation would increase patents in both the Y02C and B01D classes. In our original patent database, approximately 90% of patents tagged with the Y02C class also appear in the class B01D (2903 out of 3330 cases). This connection should blur the estimated effect of the environmental regulation between green and non-green classes.[17]

Green innovations are expanding over time in the EU. The subclass Energy (clean energy) now represents the largest class in the number of patents, followed by green patents in trans-

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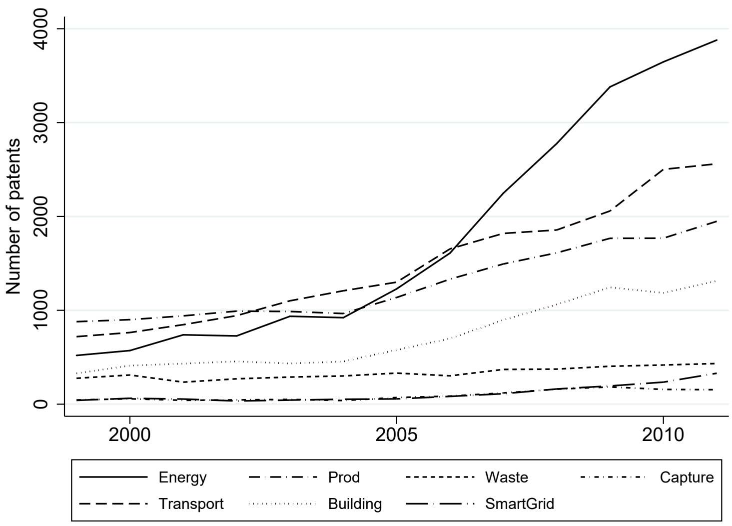
Moreover, the OECD classification relies extensively on the Y02 tagging scheme, and most of the other CPC classes are accounted for, at least partly, in our $Comp_c$ category.

[17]Put differently, this is equivalent to say that due to the interference among groups (among green and non-green classes), the response (change in patents) of an observation is related to the treatment (environmental regulation) received by other observations. Thus, this interference biases the comparison of the between-group response under treatment and no treatment.

portation (Transport) and in the production and processing of goods (Prod) (Figure 1).

Figure 1: Evolution of the number of green patents over the period 1999-2011

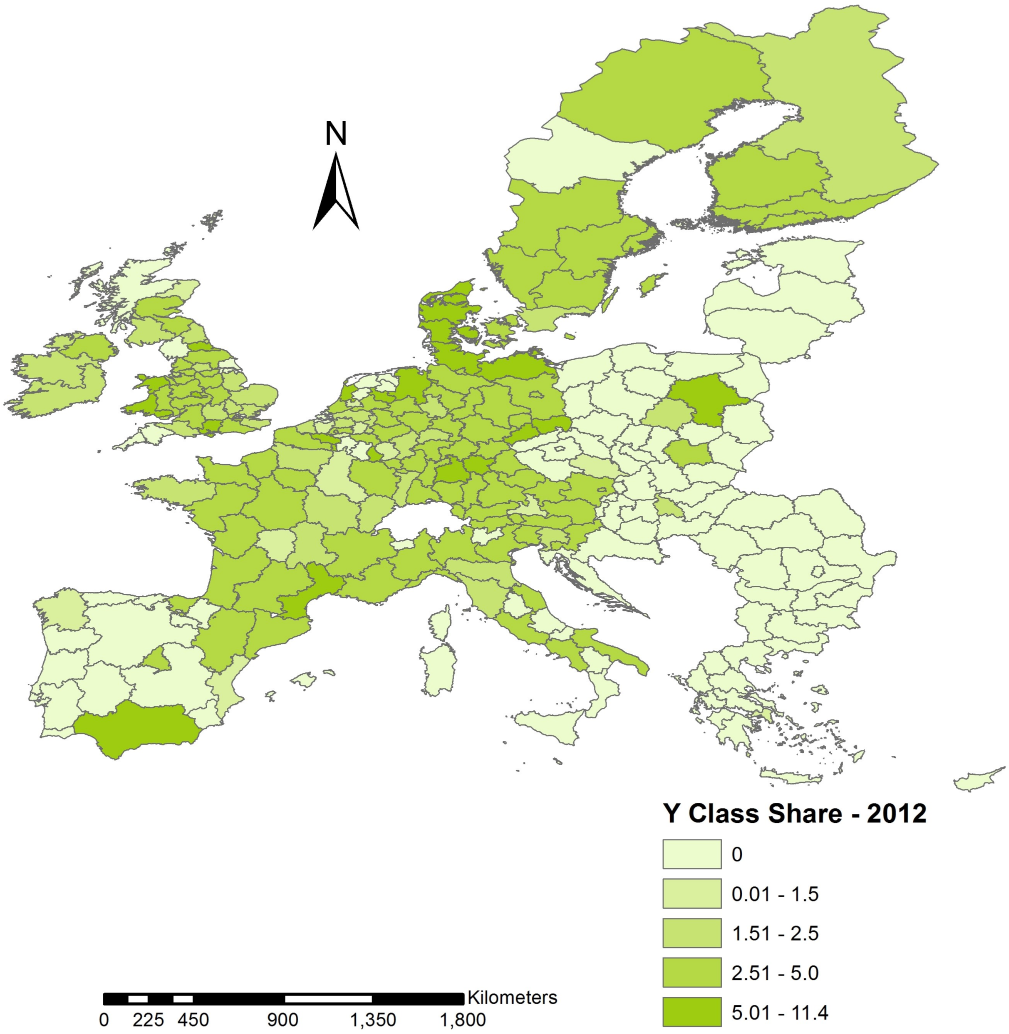


Source: PATSTAT. The number of green (CCMT) patents is computed using fractional counting (see text for details). A same patent can be tagged in several green CPC classes.

The share of green patents in the total number of patents varies significantly across EU countries. Nordic countries, such as Denmark specialising in wind energy, and some Southern or Eastern European countries, such as Greece or Romania specialising in solar energy, have a larger than average share (see Figure A2 and Table A5 in Appendix). The map displayed below (Figure 2) shows that there is also substantial heterogeneity among EU regions. Most Eastern European regions do not report any patents in green technologies or have a count of weighted patents lower than 50.[18] Nordic regions, in particular Danish regions and Northern Germany, show the highest share of green patents (higher than 5%).

[18]In the figure, we set at zero this share for regions that have a count of weighted patents fewer than 50 because in that case, a small number of green patents could tremendously increase the share of green patents in the total number of patents.

Figure 2: Average share of green patents (CCMTs) in the total number of patents by EU region in 2012



Source: PATSTAT. The number of patents is computed using fractional counting (see text for details). The zero category includes both regions that do not report any patent in CCMTs and regions that have a count of weighted patents lower than 50.

3 Results

We present our baseline results, followed by some robustness checks and additional findings from the dynamic and spatial analysis.

3.1 Baseline results

We estimate our baseline equation (eq. 1) on the overall sample, made up of 273 regions, 654 technology classes and 17 years (1999-2015). Estimation results are displayed in Table 1. The interaction between the dummy variable ($RegAQ_{rt}$) and a dummy variable identifying green patents ($Green_c$) captures the effect of measures implemented to comply with the environmental regulation on the specialisation of regions in green innovations. In columns (1) and (2), we report the results for PM10 exceedances, and in columns (3) and (4), we report the results for NO2 exceedances.[19]

We find that regions implementing environmental measures to comply with the AAQD tend to innovate more in green technologies (columns 1 and 3 of Table 1).[20] The stock of patents has the expected positive effect and is significant at the 1% level in all cases.[21]

In columns (2) and (4), we disaggregate green patents into different subclasses. Technological change triggered by environmental measures is directed more specifically towards energy

[19]In each case, the $RegAQ$ dummy variable measures exceedances of air quality limit values for each pollutant (PM10 concentration averaged over days or years; NO2 concentration averaged over hours or years) and zero otherwise. Table A6 in the Appendix reports separate estimates for exceedances of PM10 day, PM10 year, NO2 hour and NO2 year limit values.

[20]Note that our specification only allows estimating the impact of environmental regulations on green innovations compared to non-green innovations. It does not quantify the global effect of environmental regulations on innovations becaus,e in this case, the $ReqAQ_{rt}$ variable is collinear with region-year fixed effects.

[21]Estimation results are very similar when, instead of using an inverse hyperbolic sine (IHS) transformation for the patent stock variable, we use a simple log and add a dummy variable to account for observations with a lagged stock of innovations of zero (results available upon request).

Table 1: Environmental regulation and green innovations

	PM10		NO2	
	(1)	(2)	(3)	(4)
$RegAQ_{rt} \times Green_c$	0.0323*		0.0513**	
	(0.0183)		(0.0250)	
$RegAQ_{rt} \times Green_c^{Building}$		0.115***		0.0774
		(0.0434)		(0.0577)
$RegAQ_{rt} \times Green_c^{Capture}$		-0.0850		0.212
		(0.101)		(0.152)
$RegAQ_{rt} \times Green_c^{Energy}$		0.0792***		0.127***
		(0.0296)		(0.0387)
$RegAQ_{rt} \times Green_c^{Prod}$		0.0598**		0.120***
		(0.0296)		(0.0453)
$RegAQ_{rt} \times Green_c^{Transport}$		0.0251		0.0479
		(0.0377)		(0.0561)
$RegAQ_{rt} \times Green_c^{Waste}$		0.0786		0.143*
		(0.0556)		(0.0828)
$RegAQ_{rt} \times Green_c^{SmartGr}$		0.0262		0.159
		(0.0933)		(0.141)
$RegAQ_{rt} \times Comp_c$	0.0979***		0.199**	
	(0.0190)		(0.0151)	
$RegAQ_{rt} \times Comp_c^{Building}$		0.0131		0.0207*
		(0.0125)		(0.0123)
$RegAQ_{rt} \times Comp_c^{Capture}$		-0.0246**		-0.0285**
		(0.0122)		(0.0114)
$RegAQ_{rt} \times Comp_c^{Energy}$		0.0272***		0.0576***
		(0.00922)		(0.00906)
$RegAQ_{rt} \times Comp_c^{Prod}$		0.0236***		0.0269***
		(0.00881)		(0.00925)
$RegAQ_{rt} \times Comp_c^{Transport}$		0.00182		0.0923***
		(0.0116)		(0.0110)
$RegAQ_{rt} \times Comp_c^{Waste}$		0.0259**		0.0603***
		(0.0103)		(0.00899)
$RegAQ_{rt} \times Comp_c^{SmartGr}$		0.106***		0.103***
		(0.0123)		(0.0128)
$Patents\ Stock_{rct-1}$	0.216***	0.215***	0.211***	0.210***
	(0.0115)	(0.0114)	(0.0115)	(0.0113)
Observations	1,198,944	1,198,944	1,198,944	1,198,944
Region-class FE	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes
Class-year FE	yes	yes	yes	yes

Notes: The dependent variable is the weighted count of patents per EU region, class and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

sources alternative to fossil fuels (${Green_c}^{Energy}$) and green innovations in the production or processing of goods (${Green_c}^{Prod}$). These two technology classes represent approximately half of all green patents. We also observe increasing green innovations in buildings (${Green_c}^{Building}$) for air quality measures targeting PM10 and in waste and wastewater (${Green_c}^{Waste}$) for measures targeting NO2. This result is consistent with pollutant-specific sources: the construction of buildings and infrastructure is a substantial source of PM10 emissions, while waste incineration and wastewater treatment cause NO2 emissions. Interestingly, we do not find any effect of air pollution regulation on green innovations in transportation (${Green_c}^{Transport}$), which is a major contributor to air pollution and one of the largest classes of green patents (see Figure 1 and Table A5 in Appendix). One possible reason is that innovations in this class are driven by country-wide policies targeting the automotive industry (such as car emission standards or tax-inclusive fuel prices, see Aghion et al. 2016).

Our estimates show that environmental measures increase patents tagged as green but also patents that belong to complementary technological classes. The coefficient on the variable $RegAQ_{rt} \times Comp_c$ is positive and significant (columns 1 and 3), and this conclusion holds for many subclasses (classes complementary to *Energy*, *Prod*, *Waste* and *SmartGrids*) (columns 2 and 4). Environmental measures targeting NO2 also boost innovations in classes complementary to green technologies in transportation (${Comp_c}^{Transport}$). While environmental measures do not seem to directly affect green innovations in transportation (making transportation more efficient or less carbon-intensive, for instance), these results suggest that they seem to affect related non-green technologies.

In terms of magnitude, our baseline coefficient estimates indicate that environmental measures targeting PM10 emissions increase green innovations by 8.2% [=exp(0.0792)-1] in energy and by 6.2% [=exp(0.0598)-1] in the production or processing of goods in regulated regions compared to unregulated regions (column 2). For measures targeting NO2, the effects are larger, approximately 13.5% for innovations in clean energy and 12.7% for green innovations in the production or processing of goods (column 4). This direct effect should also foster a greener technological path in regulated regions. Indeed, considering the path dependence in the innovation process, air quality regulation should increase green innovations beyond its contemporaneous effect, through an increase in the stock of green patents. Suppose a region that implements environmental measures only in the year after entry into force of the limit value (2005 for PM10). Then, the cumulative effect for clean energy innovations after 10 years is estimated to be 15.8% [$= 0.082 + \sum_{k=0}^{8} 0.215 * 0.082 * 0.8^k$]. For green patents in industrial processes, the respective cumulative effect is approximately 12%. Suppose now a region that implements environmental measures targeting NO2 in 2010 (the year of the entry into force of NO2 limit values); then, the cumulative increase in innovations in clean energy would be 25.8% after 10 years [$= 0.135 + \sum_{k=0}^{8} 0.21 * 0.135 * 0.8^k$] and 24.2% for green innovations in the production or processing of goods.

A back-of-the-envelope computation can provide insight into the number of extra green patents generated by the AAQD. In our dataset, we have a total of 11,662 patents in clean energy and 7,546 green patents in the production or processing of goods in regulated regions (exceeding PM10 limit values) over the 2005-2015 period. Using the world without policy as our baseline, these estimation results imply that the regulation immediately induces 1,324 [$= (11,662 - 11,662/(1 + 0.082)) + (7,546 - 7,546/(1 + 0.062))$] new patents in clean energy and industrial processes in regulated regions compared to non-regulated regions and 2,400 [$= (11,662 - 11,662/(1 + 0.158)) + (7,546 - 7,546/(1 + 0.12))$] new green patents after 10 years. NO2-related measures should generate 1,979 new green patents as a direct effect and up to 3,416 over 10 years.[22]

3.2 Robustness analysis

To test the robustness of our results with respect to the environmental regulation variable, we estimate our model on several subsamples. We first exclude regions that never exceeded over the whole time span (1999-2015). These regions are used in the control group in our baseline estimations but we might think that they are intrinsically different from regions that

[22] $1,979 = (10,896 - 10,896/(1 + 0.135)) + (6,062 - 6,062/(1 + 0.127))$ and $3,416 = (10,896 - 10,896/(1 + 0.258)) + (6,062 - 6,062/(1 + 0.242))$, given that the total number of green patents in regulated regions over the 2010-2015 period is 10,896 in clean energy and 6,062 in industrial processes.

exceeded at least once. In our original sample, we have 273 regions. Among these, 80 regions from 15 countries never exceeded PM10 limit values. These regions are located mainly in the UK for 45% and in France for 11%. When excluding regions that did not have to implement any PM10-related environmental measures to comply with the AAQD because they never exceeded limit values, our estimates provide a sort of 'treatment effect among the treated'. The results are displayed in column (1) of Table 2. They are close to the baseline estimates (column 2 of Table 1). Similarly, we exclude regions that never exceeded NO2 limit values (114 regions located in 25 EU countries) in column (2) and obtain similar results.

We further investigate the robustness of our results with respect to the *RegAQ* variable. Regulations other than the AAQD at the EU, national or subnational levels are controlled for in the estimation with region-year fixed effects. However, if these other regulations are correlated with AAQD exceedances (our measure of the regulation), then our coefficient of interest might be biased. There is no obvious reason why this should happen in the case of a regulation that has nothing to do with the Air Quality Directive. However, we still want to check the robustness of our results controlling for the other major regulations against pollution, the NECD (see section 2.2). More precisely, we estimate our model on regions of countries that never exceeded their national emission ceilings for NOx over the post-2010 period, when the NECD entered into force.[23] This represents 10 countries (out of 28) that should not have implemented any further actions or programmes to reach NECD targets. Estimation results on this subsample (column 3 of Table 2) yield similar conclusions.

We also check the robustness of our results with respect to infringement cases. As stated before, the AAQD is a relatively effective regulation and most countries and regions implement environmental measures in case of exceedances. However, one can still argue that some member states fail to comply because the regulation is not implemented forcefully in all regions. Indeed, the European Commission (EC) currently pursues infringement proceedings at various stages on NO2 and PM10 against several member states and referred eight

[23]The NECD also concerns three other pollutants that we do not consider here, i.e. non-methane volatile organic compounds (NMVOCs), sulphur dioxide (SO2), ammonia (NH3) and, after 2016, fine particulate matter (PM2.5).

Table 2: Environmental regulation and green innovations - Robustness checks

	Without Non-Exc Reg.		No NECD Ex	No Infringements		With Polut. level	
	PM10	NO2	NO2	PM10	NO2	PM10	NO2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$RegAQ_{rt} \times Green_c{}^{Building}$	0.140***	0.0920	0.0114	0.119***	0.178***	0.114***	0.0811
	(0.0473)	(0.0788)	(0.0747)	(0.0449)	(0.0675)	(0.0443)	(0.0583)
$RegAQ_{rt} \times Green_c{}^{Capture}$	-0.0641	0.242	0.557***	-0.115	0.00581	-0.0481	0.212
	(0.103)	(0.217)	(0.206)	(0.102)	(0.187)	(0.108)	(0.157)
$RegAQ_{rt} \times Green_c{}^{Energy}$	0.116***	0.259***	0.0851*	0.0860***	0.0719	0.0641**	0.121***
	(0.0318)	(0.0597)	(0.0496)	(0.0302)	(0.0503)	(0.0297)	(0.0385)
$RegAQ_{rt} \times Green_c{}^{Prod}$	0.0769**	0.147**	0.234***	0.0707**	0.0972*	0.0608*	0.116**
	(0.0325)	(0.0659)	(0.0605)	(0.0313)	(0.0566)	(0.0325)	(0.0465)
$RegAQ_{rt} \times Green_c{}^{Transport}$	0.0647	0.119	0.0465	0.0271	0.131*	0.0517	0.0591
	(0.0421)	(0.0771)	(0.0704)	(0.0386)	(0.0720)	(0.0394)	(0.0569)
$RegAQ_{rt} \times Green_c{}^{Waste}$	0.107*	0.0189	0.130	0.0627	0.0668	0.0535	0.145*
	(0.0617)	(0.113)	(0.103)	(0.0581)	(0.0964)	(0.0600)	(0.0832)
$RegAQ_{rt} \times Green_c{}^{SmartGr}$	0.0691	0.192	0.118	0.0569	0.0309	-0.0001	0.139
	(0.0980)	(0.214)	(0.198)	(0.0953)	(0.153)	(0.0992)	(0.140)
$\ln MeanPol \times Green_c{}^{Building}$						0.101	-0.0099
						(0.127)	(0.0942)
$\ln MeanPol \times Green_c{}^{Capture}$						-0.186	0.0537
						(0.311)	(0.351)
$\ln MeanPol \times Green_c{}^{Energy}$						0.291**	-0.0279
						(0.117)	(0.0919)
$\ln MeanPol \times Green_c{}^{Prod}$						0.145	0.131*
						(0.0924)	(0.0775)
$\ln MeanPol \times Green_c{}^{Transport}$						-0.261**	-0.0999
						(0.110)	(0.0903)
$\ln MeanPol \times Green_c{}^{Waste}$						-0.0872	-0.330***
						(0.157)	(0.113)
$\ln MeanPol \times Green_c{}^{SmartGr}$						0.301	-0.00735
						(0.420)	(0.259)
$Patents\ Stock_{rct-1}$	0.245***	0.245***	0.203***	0.226***	0.142***	0.185***	0.210***
	(0.0134)	(0.0127)	(0.0120)	(0.0119)	(0.0155)	(0.0128)	(0.0116)
Observations	818,748	876,681	800,384	1,101,428	809,342	1,060,419	1,139,746
Control $RegAQ_{rt} \times Comp_c$	yes	yes	yes	yes	yes	yes	yes
Region-class FE	yes	yes	yes	yes	yes	yes	yes
Class-year FE	yes	yes	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the weighted count of patents per EU region, class and year. Robust standard errors clustered at the region-year in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include interaction terms between the $RegAQ$ variable and a dummy $Comp_c$ capturing whether a non-green technology class is complementary to each green class, as defined by the Y02/Y04S tagging scheme (unreported).

countries to the European Court of Justice (ECJ) (second to last stage of the procedure) for systematic and continuous exceedance in several regions. This means that the EC and/or the ECJ considers that these regions did not implement sufficient measures to reduce pollution. Therefore, as a robustness check, we redo the estimation on subsamples excluding these 37 regions in 5 countries (Bulgaria, Poland, Hungary, Italy, Romania) that have been referred to the ECJ for not complying with the AAQD for PM10 and 53 regions in 3 countries (France, Germany and the United Kingdom) for NO2.[24] Estimations on these subsamples reported in columns (4) and (5) show broadly similar results. Regulated regions seem to engage in relatively more green innovations in clean energy and in the production or processing of goods.

Additionally, we control for the existence of potentially omitted variables. In columns (6) and (7) of Table 2, we include as additional control variables the annual mean concentration of pollution in PM10 and NO2 per region and year interacted with the dummy variables identifying green patents.[25] This allows us to test whether our variable measuring exceedances of limit values is a good proxy for changes in environmental regulation and does not capture only the level of pollutant concentration. As in our baseline results, we still find that our interaction variable for environmental regulation remains positive and significant for clean energy (${Green_c}^{Energy}$) and green technologies in the production or processing of goods (${Green_c}^{Prod}$).

Then, we test the robustness of our results with respect to extreme cases: regions that always exceed air quality limit values or regions with very high pollution levels. In Appendix Table A7, we reestimate our model, first, on the sample excluding regions that always exceed over the sample period (1999-2015).[26] Then, we exclude the 10% most polluting regions in our sample (26 regions) for PM10 and for NO2 concentration levels. In all cases, our main

[24]To identify these regions, we use information from the Official Journal of the European Union and create a spatial concordance between air quality zones and NUTS-2 regions.

[25]Note that, in this specification, the level of pollutants concentration is captured by region-year fixed effects. For this reason, we only add the interaction between this variable and dummies for green technologies.

[26]This represents 40 regions for PM10 located mainly in Poland (30%), Italy (17%) and in the Czech Republic (15%) and 77 regions for NO2 mainly in Germany (38%).

conclusions remain.

Finally, we use an alternative variable that measures the stringency (intensity) of environmental measures: the average exceedance level above the limit value (average number of days or times of exceedance by region and year) over the allowed level. The estimation results, reported in Table A8 in the Appendix, provide similar conclusions. We find that environmental measures foster green innovations mostly in clean energy and in industrial processes.[27]

3.3 Placebo

We further implement a set of placebo tests to investigate the validity and robustness of our research design. The AAQD implies a discontinuity in the treatment: a region should be 'treated' (i.e., implement additional environmental measures) *when* it exceeds predefined yearly thresholds of pollution concentration (see section 2.2 and Table A2 in the Appendix). For each pollutant, we define placebo threshold values of pollution concentrations that are close but lower than official levels as defined by the AAQD. We construct region-year dummies for 'placebo-treated' regions (placebo limit values are given in Appendix Table A3). As these regions do not fall within the scope of the AAQD, they should not depict increased specialisation in green technologies.

We first ran our placebo analysis on our baseline sample of regions. These results are reported in columns (1) and (2) for PM10, and (5) and (6) for NO2 in Table 3. As anticipated, the estimated placebo treatment effect is small or negative in magnitude and statistically indistinguishable from zero. Regions that fall within the placebo treatment have slightly negative green specialisation on average (columns 1 and 5), but corresponding coefficients are not statistically significant.

To test how the placebo-treated regions behave in comparison to other nontreated nor placebo-treated regions, we exclude region-years that exceed limit values as defined by the

[27]Note that estimation results point to some negative effects of additional measures against PM10 emissions on green innovations in carbon capture (${Green_c}^{Capture}$) and smart grids (${Green_c}^{SmartGr}$), but these should be considered with caution because the number of patents in these categories is much smaller.

AAQD regulation for PM10 (columns 3 and 4) and NO2 (columns 7 and 8). If our model is well specified, we should find no effect of the placebo compared to those regions having lower levels of pollution concentration. As anticipated, the estimated placebo effects are not significantly different from zero at conventional levels. These results combined with those from Table A7 suggest that the estimated increase in green innovations in Table 1 does not arise from gross misspecification in our research design. We observe a positive effect on green innovation specialisation only when a region exceeds those pollution concentration levels that necessitate implementing further environmental measures. This also provides further evidence endorsing that AAQD air pollution exceedances actually translate into additional measures.

3.4 Dynamic analysis

In our analysis, we find direct and contemporaneous impacts of air quality exceedances on green innovations. However, local or national authorities might also implement mid- or long-term measures, or might implement measures only some time after the exceedances of air quality limit values. Innovations might also react with delays or by anticipation. For these reasons, in this section, we further analyse the timing of green innovation response to environmental measures faced by regions under the AAQD. To test for the impact of exceedances over time, we estimate our model introducing one- to three-year lags and leads for the exceedance variable (interacted with the *Green* dummy variables as before).[28] Estimation results are presented graphically in Figure 3. For clarity, we report only the key estimated coefficients on the lags and leads for the two patent subclasses of interest (green innovations in clean energy and in industrial processes).

Our results suggest both contemporaneous and lagged effects on green innovations. There is a significant response of green patenting specialisation sustained up to three years after the environmental policy shock. We observe no positive response prior to the shock, none of

[28] In these estimations, the stock of patents is lagged four years to stay consistent with our underlying model.

Table 3: Placebo regulation and green innovations

	Baseline	Baseline	Without Exceeding Regions		Baseline	Baseline	Without Exceeding Regions	
	PM10	PM10	PM10	PM10	NO2	NO2	NO2	NO2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PlaceboReg_{rt} \times Green_c$	-0.0247		-0.0445*		-0.0123		0.0152	
	(0.0163)		(0.0228)		(0.0383)		(0.0445)	
$PlaceboReg_{rt} \times Green_c^{Building}$		-0.0554		-0.0590		-0.0123		-0.0131
		(0.0380)		(0.0535)		(0.0792)		(0.0928)
$PlaceboReg_{rt} \times Green_c^{Capture}$		0.121		0.0638		-0.269		-0.147
		(0.0921)		(0.144)		(0.237)		(0.250)
$PlaceboReg_{rt} \times Green_c^{Energy}$		0.00530		0.0150		0.0331		0.0812
		(0.0246)		(0.0364)		(0.0607)		(0.0669)
$PlaceboReg_{rt} \times Green_c^{Prod}$		0.0202		0.0516		0.0396		0.131
		(0.0278)		(0.0413)		(0.0692)		(0.0794)
$PlaceboReg_{rt} \times Green_c^{Transport}$		0.00920		-0.0487		-0.0178		-0.0300
		(0.0371)		(0.0488)		(0.0749)		(0.0963)
$PlaceboReg_{rt} \times Green_c^{Waste}$		0.0572		0.132*		0.0424		0.183
		(0.0528)		(0.0722)		(0.131)		(0.151)
$PlaceboReg_{rt} \times Green_c^{SmartGr}$		0.0465		0.0427		0.0928		0.246
		(0.0796)		(0.121)		(0.193)		(0.211)
$Patents\ Stock_{rct-1}$	0.216***	0.216***	0.216***	0.216***	0.217***	0.217***	0.0829***	0.0826***
	(0.0115)	(0.0115)	(0.0142)	(0.0141)	(0.0115)	(0.0115)	(0.0157)	(0.0156)
Observations	1,198,944	1,198,944	871,352	871,352	1,198,944	1,198,944	929,328	929,328
Control $PlaceboReg_{rt} \times Comp_c$	yes	yes	yes	yes	yes	yes	yes	yes
Region-class FE	yes	yes	yes	yes	yes	yes	yes	yes
Class-year FE	yes	yes	yes	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the weighted count of patents per EU region, class and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include interaction terms between the $PlaceboReg$ variable and a dummy $Comp_c$ capturing whether a non-green technology class is complementary to each green class, as defined by the Y02/Y04S tagging scheme (unreported). In Columns 3 - 4 and 7 - 8 we report results on estimations when excluding region-years that exceed official limit values as defined by the AAQD regulation, respectively for PM10 (Col. 3 and 4) and NO2 (Col. 7 and 8).

the preshock coefficients are significantly different from zero. Thus, there do not seem to be any anticipation effects, further suggesting that the AAQD generates an exogeneous shock to local environmental measures. Consistent with our baseline results, the impact of NO2-related measures is stronger and longer lasting than that of PM10. Overall, green innovations are more affected in the year of exceedances and in the year after, but there are also significant effects two to three years after the exceedances (PM10 exceedances for innovations in clean energy and NO2 exceedances for green innovations in the production or processing of goods). Note that the dynamic effects of the regulation seem to be less clear-cut for innovations in industrial processes, both for PM10 and NO2 (bottom graphs).[29]

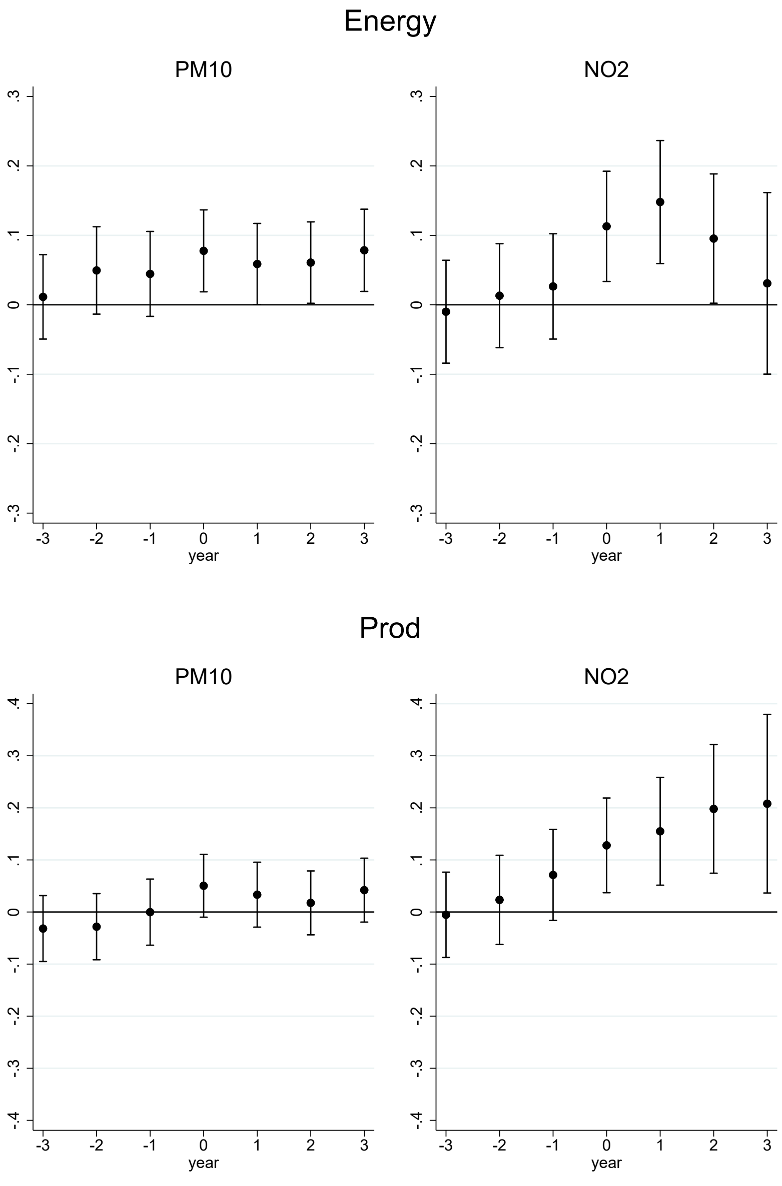
3.5 Spatial analysis

In this subsection, we undertake some spatial analyses. Local green innovations might respond to broader incentives, as environmental measures implemented in one region could induce more green patents in other (close) regions. This could occur in particular if the effect of the regulation on innovation is indirect, driven by an increase in the demand for green technologies. Conversely, innovators might engage in more green innovations in regulated regions but less so in neighbouring unregulated regions due to potential substitution or spatial leakage effects. To further investigate the geographical pattern of innovations and discriminate between these two possible effects, we introduce regional spatial dynamics with an additional variable evaluating the extent to which neighbouring regions have to implement further environmental measures under the AAQD. More precisely, we construct for each region a variable capturing the distance-weighted regulation of other regions (q) in the country:

$$RegAQ_{-rt} = \frac{\sum_{q\neq r} RegAQ_{qt} \times (1/Dist_{qr})}{\sum_{q\neq r}(1/Dist_{qr})}$$

[29]The lagged effects of PM10-related measures are marginally significant and the lagged effects of NO2-related measures seem to reflect an increasing trend. However, estimates of the lagged variables are generally less precise, and we cannot investigate longer lags of the innovation response to the AAQD, in particular for NO2-related measures because NO2 limit values entered into force in 2010 and the period of our dataset ended in 2015.

Figure 3: The dynamic effect of the regulation on innovations in clean energy ($RegAQ{\times}Green^{Energy}$) and industrial processes ($RegAQ{\times}Green^{Prod}$)



Source: Own estimation results (see text for details). The vertical bars refer to the 95% confidence interval. The horizontal axis represents the number of years before and after exceedances of air quality limit values (PM10 or NO2).

The corresponding variable takes values between 0 and 1. It is 0 when no other regions of the country need to implement environmental measures due to exceedances of the limit values in a given year. It is 1 when all other regions of the country need to implement further measures. Its value is closer to 1 when close regions exceed compared to more distant regions. By adding this variable in equation (1) (interacted with the *Green* dummy variables as before), we measure the specialisation in green innovations of each innovative region when other regions in the country implement additional environmental measures.

Table 4: Environmental regulation and green innovations - Spatial anaysis

	PM10		NO2	
	Region reg ($RegAQ_{rt}$)	Rest of cty reg ($RegAQ_{-rt}$)	Region reg ($RegAQ_{rt}$)	Rest of cty reg ($RegAQ_{-rt}$)
	(1)	(2)	(3)	(4)
$RegAQ_{rt}$ or $RegAQ_{-rt}$				
$\times Green_c{}^{Building}$	0.0642	0.281***	0.0805	-0.0681
	(0.0469)	(0.0992)	(0.0659)	(0.0960)
$\times Green_c{}^{Capture}$	-0.126	0.261	0.0559	0.519**
	(0.104)	(0.265)	(0.163)	(0.235)
$\times Green_c{}^{Energy}$	0.0863***	-0.201***	0.107**	0.0396
	(0.0305)	(0.0754)	(0.0455)	(0.0699)
$\times Green_c{}^{Prod}$	0.0672**	-0.158**	0.0981*	0.0226
	(0.0325)	(0.0793)	(0.0547)	(0.0814)
$\times Green_c{}^{Transport}$	0.0257	-0.192*	0.0474	-0.125
	(0.0392)	(0.105)	(0.0631)	(0.0998)
$\times Green_c{}^{Waste}$	0.0684	0.0302	0.126	-0.0154
	(0.0612)	(0.136)	(0.0858)	(0.124)
$\times Green_c{}^{SmartGr}$	0.0768	-0.729**	0.119	0.0526
	(0.0946)	(0.305)	(0.148)	(0.229)
$Patents\ Stock_{rct-1}$	0.216***		0.211***	
	(0.0114)		(0.0113)	
Observations	1,193,909		1,193,909	
Control $RegAQ_{rt} \times Comp_c$	yes		yes	
Control $RegAQ_{-rt} \times Comp_c$	yes		yes	
Region-class (rc) FE	yes		yes	
Class-year (c_1t) FE	yes		yes	
Region-year (rt) FE	yes		yes	

Notes: The dependent variable is the weighted count of patents per EU region, class and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include interaction terms between the $RegAQ_{rt}$ (or $RegAQ_{-rt}$) variable and a dummy $Comp_c$ capturing whether a non-green technology class is complementary to each green class, as defined by the Y02/Y04S tagging scheme (unreported).

Estimation results are displayed in Table 4. The positive effect of the regulation on green innovations in clean energy (${Green_c}^{Energy}$) and in the production or processing of goods (${Green_c}^{Prod}$) are mainly local (columns 1 and 3). Environmental measures in other regions have either no impact on specialisation in green innovations (column 4) or a negative one (column 2). This last result might suggest substitution effects. Some environmental measures might trigger local green innovations but at the same time reduce green innovations in proximate regions (as compared to non-green innovations). Note that we obtain very similar results when the variable for the regulation in other regions ($RegAQ_{-rt}$) is not weighted by distance (see Table A9 in the Appendix).

These findings suggest that estimating our equation at the country level can blur the identification of the AAQD effect by 'hiding' specific effects occurring at the regional level if there are substitution effects between innovating regions. On the other hand, even if most environmental measures to comply with the Air Quality Directive are defined at the local or regional levels, some of them are implemented on a national basis. More specifically, it is countries, and not regions, that are accountable to the European Commission for effectively transposing and implementing this directive nationally.[30] Therefore, the full constraint imposed by the regulation could be perceived at the country level.

In Table A10 in the Appendix, we redo our baseline estimation at the country level. The estimation results are generally consistent with the preceding analysis. At the country level, we find no effect of measures against PM10 on green innovations (column 1) or on green innovations in clean energy or in industrial processes (column 2). This could be because positive effects on the regulated regions are counteracted by negative effects in close regions of the same country (see columns 1 and 2 in Table 4). On the other hand, environmental measures targeting NO2 still induce more green innovations in clean energy at the country level because in that case, we do not see any substitution effect with other regions (see columns 3 and 4 in Table 4).[31]

[30]For example, when the European Commission considers that the regulation is not enforced, it launches legal proceedings against countries.

[31]Note that the estimated effect of environmental measures on non-green but related technologies ($Comp_c$)

Finally, we introduce as an additional control variable the stock of patents for a given technology class in other regions of the same country weighted by geographic distance. The results are displayed in Table A11 in the Appendix. Local specialisation in specific technologies also depends upon the stock of patents in other regions. The coefficients of local and rest-of-the-country stocks of patents are consistent with the one displayed in the country-level analysis (Table A10 in the Appendix). Moreover, we still find a positive effect of environmental measures on regional specialisation in green innovations in clean energy and in industrial processes.[32]

4 Endogeneity

To identify a causal effect, our empirical strategy focuses on the interaction between a technology feature (green vs. non-green) and an exogenous policy feature at the region level (additional environmental measures in the region-year due to the exceedance of a pollution threshold). This allows controlling for a large set of fixed effects – at the region-technology class, region-year and technology class-year levels – producing an identification strategy that follows the same rationale as a quasi difference-in-difference setting. However, to be interpreted as causal, the interaction with our main policy variable ($RegAQ$) should not suffer from an endogeneity bias and thus needs to fulfil a set of assumptions.

There are two main suspects as a source of endogeneity in our baseline estimates. First, regions with "greener" activity (and greener innovations) could also be less likely to exceed pollution thresholds requiring the implementation of further environmental regulations. This source of reverse causality should bias our estimates downward.[33] The second concern is the

are very similar at the regional and country levels because environmental measures do not induce substitution effects in other regions for these technologies.

[32]When we assess the impact of environmental measures in proximate regions, controlling for the stock of patents in these other regions, we do find very similar results (see Table A12 in the Appendix compared to Table 4).

[33]Note that our robustness analysis (subsection 3.2), by excluding from the sample regions that have

latitude granted to countries and regions in choosing measures to be implemented in case of exceedance. A potential source of omitted-variable bias could arise from polluting sector lobbying if economic sectors generating relatively more non-green innovations are also those responsible for higher pollution. Lobbying from key local sectors could push local authorities to not implement the most coercive measures incumbent upon the most polluting sectors.

In both cases, the sources of potential endogeneity go against our testing assumption and should bias our results downward. We further investigate whether our previous results underestimate the impact of environmental regulation on specialisation in green innovations.

To tackle the endogeneity issue and test for the direction of its bias, we use an exogenous instrument. We follow Broner et al. (2012) and Bagayev and Lochard (2017) and instrument the exceedance of air pollutant concentration levels by a measure of the speed at which pollutants disperse in the air due to meteorological conditions. More specifically, we compute ventilation coefficients that multiply wind speed and the depth of the atmospheric layer. This type of ventilation coefficient is commonly used in meteorological forecasts to predict the levels and concentration of air pollution in a region. ERA-Interim data from the European Centre for Medium-Term Weather Forecasting (ECMWF) make available wind and mixing layer information in the very short term (daily basis) and at a very local level (areas representing less than 10 square kilometres, on average). Using geographic coordinates of the stations that serve to monitor air pollution concentration levels under the AAQD, we thus compute the minimum monthly average ventilation coefficient faced by any monitoring station at a region-year level. As previously shown in Bagayev and Lochard (2017), the ventilation coefficient is a good predictor of exceedance of air pollutant concentration and is very plausibly exogenous to local economic factors.

never exceeded air quality limits during our time frame (columns 1 and 2 in Table 2), sheds some light on this issue. The larger estimates in columns (1) and (2) are consistent with the idea that regions that have no pollutant exceedances tend to have greener innovation specialisation, which can be a source of reverse causality. However, this endogeneity bias could be more important than suggested by the robustness check in Table 2 due to the within-region yearly variations in green innovation that can, in turn, influence the probability of exceeding pollutant concentration levels.

The estimation of our econometric specification through the instrumental variables method is complicated because the second-stage specification is non-linear and includes high dimensional fixed effects (more than 90,000 fixed effects). Thus, we need to rely on an alternative strategy and adopt a two-stage residual inclusion (2SRI) control function approach (Wooldridge, 2015).

The results from the control function approach are reported in Table 5. It should be noted that there are some notable differences in the estimations of Table 5 compared to our baseline estimations. First, our first-stage estimations cannot include both region-year and region-class fixed effects due to multicollinearity.[34] Accordingly, we do not use region-class fixed effects but instead rely on country-class fixed effects. Second, the sample size is somehow smaller than our main estimations due to missing geographic coordinates of some monitoring stations. Therefore, as a matter of comparison, we include estimates of our baseline equation using the same restricted sample (columns 1 and 3).[35] Finally, note as well that our control function approach does not allow disaggregating the *Green* class into several subclasses because we only have one instrument. For the same reason, we cannot control for the interaction of the environmental regulation variable with the dummy for classes complementary to green technologies ($RegAQ{\times}Comp$).

The coefficients of our main variable of interest in columns (1) and (3) are very similar to our baseline estimates reported in Table 1 (columns 1 and 3).[36] The stock of patents depicts a larger coefficient due to the use of country-class fixed effects (instead of region-class fixed effects). This variable now captures the initial cross-technology class differences between regions that were previously captured by the region-class fixed effects. The control function

[34]The first-stage dependent variable is dichotomous (the interaction between $RegAQ_{rt}$ and $Green_c$).

[35]The estimation routine drops singletons to improve the convergence of the maximum likelihood coefficients. Indeed, in the first stage, when residuals to be included in the second stage are calculated, the routine drops region-year observations for which the dependent variable is always zero. This results in a slight decrease in the number of observations between columns (1) and (3) and columns (2) and (4).

[36]Contrary to Table 1, estimations of columns (1) and (3) of Table 5 do not include $RegAQ{\times}Comp$. Doing so provides very similar but slightly larger coefficients. We do not report these estimations, but they are available upon request.

estimates are presented in columns (2) and (4), with the first-stage estimates provided at the bottom of Table 5. First, it can be noted that the ventilation coefficient has a negative and highly significant effect on the exceedance of both PM10 and NO2 limit values. As expected, higher ventilation in a region decreases the probability of exceeding pollutant concentration levels, which seems to support the use of this instrument in our specification. The residuals from the first-stage estimations of the $RegAQ \times Green$ variable are then included in our baseline estimates. These residuals should capture all the endogenous components of our variable of interest and leave out only the exogenous component predicted by the instrument. When included in the second stage, residuals depict highly negative and significant coefficients, suggesting a downward bias in our previous estimations. Indeed, the effect of environmental stringency on specialisation in green innovations is much larger using the control function. Supporting our main finding, these results also indicate that our previously reported impact of environmental regulation on specialisation in green innovations is likely to be underestimated.

Table 5: Environmental regulation and green innovations - Control function

	PM10		NO2	
	Poisson	2SRI	Poisson	2SRI
	(1)	(2)	(3)	(4)
$RegAQ_{rt} \times Green_c$	0.0331**	0.476***	0.0502**	0.644***
	(0.0167)	(0.155)	(0.0248)	(0.198)
$\ln Patents\ Stock_{rct-1}$	0.822***	0.822***	0.822***	0.822***
	(0.00339)	(0.00339)	(0.00339)	(0.00339)
Control Function Residuals:				
$RegAQ_{rt} \times Green_c$ (residual)		-0.450***		-0.600***
		(0.158)		(0.200)
	1st Stage Dep. var: $RegAQ_{rt} \times Green_c$			
$Ventilation\ Coeff_{rt} \times Green_c$		-0.0880***		-0.0686***
		(0.0177)		(0.0133)
Observations	1,175,107	1,175,058	1,175,107	1,175,058
Country-class FE	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes
Class-year FE	yes	yes	yes	yes

Notes: The dependent variable is the weighted count of patents per EU region, class and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The control function approach is applied to the estimations reported in columns (2) & (4). The exogenous instrument used in the first stage is the log of the minimum monthly ventilation coefficient (interacted with the dummy $Green_c$). The first stage dependent variable is respectively the RegAQ dummy (interacted with the dummy $Green_c$) when a region exceeds the limit values for PM10 concentration (column 2) and NO2 concentration (column 4). See text for details.

5 Final remarks

Local air pollution regulations can both protect human health, as well as mitigate global climate change. However, the effectiveness of these regulations to counter climate change is subject to their impact on redirecting technological change towards green technologies.

Our analysis shows a positive and significant effect of environmental measures on specialisation in green innovations in general. We also find some differential impacts depending on the class of green innovations, with a strong and positive effect for green innovations in clean energy, in the production or processing of goods and, to a lesser extent, in buildings and in waste and wastewater. We do not find consistent results supporting a positive effect of the regulation on green innovations in transportation.

We bring important policy implications through our analysis. Our findings show that environmental regulation fosters technological change towards climate change mitigation. This is all the more important since the effectiveness of environmental regulations to generate green innovations is central to anticipating the cost of mitigating climate change. It also brings further evidence of the trade-off between the environmental and economic benefits of environmental measures. In particular, policy measures to fight air pollution, which has both sizeable economic and human health impacts, have a generally positive effect on innovations that aim at slowing down climate change and its consequences.

In our analysis, we are able to evaluate the overall impact of additional environmental measures implemented to comply with European regulations. However, our environmental regulation variable does not allow us to compare the effects of different policy instruments on green innovations. Moreover, the CCMT tagging scheme does not identify the degree to which technologies are 'environmentally friendly'. Finally, our analysis mainly focuses on the demand side and does not comprehensively investigate the process of generating innovations, in particular the cost of innovation in different technology fields.

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