Innovation in climate change mitigation technologies and environmental regulation

Final Report

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Research Theme:	Patents and climate change mitigation technologies
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Executive summary

- Air pollution is a major issue in terms of its impacts on human health, ecosystems and climate change. The European Union has undertaken increasing efforts to decrease air pollution and it is now one of the most regulated area in the world. Despite obvious positive environmental benefits, the existing evidence strongly indicates that the implementation of environmentally stringent regulations is not cost free in terms of economic activity.

- Analyzing the impact of these regulations on the level and direction of technological change is thus of primary importance from a policy perspective. The current project intends to improve the understanding of how environmental regulations direct technological change and spurs additional innovations in Climate Change Mitigation Technologies (CCMTs).

- We implement a quasi difference in differences setting to test for the effect of environmental measures on innovation at the EU region (NUTS-2) level over the 1999-2015 period. Our proxy variable for environmental regulation is based on the major European regulation to fight air pollution (the Ambiant Air Quality Directive). To measure innovations, we rely on EPO's PATSTAT database. We use annual counts of patent applications at the 4-digit CPC class level based on the date of priority.

- We find a positive effect of environmental measures on specialisation in CCMTs in general. Our results also depict non-homogenous reactions to the regulation. We find a positive effect for innovations in clean energy, in CCMTs in energy intensive industries and, to a lesser extent, in buildings and in waste and wastewater. We do not find any effect of the regulation on CCMTs in transportation.

- We also show that our results are robust to a number of sensitivity tests and we further investigate the impact of the regulation overtime and over different regions in order to understand the geographical pattern of innovation. Last but not least, we show that the positive impact of the environmental regulation on innovations might be underestimated due to a downward endogeneity bias.

- Our analysis has some important policy implications. It does provide some new evidence of the benefits of environmental regulation, and in particular air pollution regulation, on fostering technological change towards climate change mitigation. It also gives further arguments to fuel the debates about the economic cost of fighting climate change and the trade-off between environmental and economic gains of environmental measures.

1 Introduction

The scientific evidence for human induced climate change and environmental degradation is unequivocal (IPCC, 2014). The forecasted costs associated with global warming, the exhaustion of natural resources and air pollution are particularly alarmist. But, impacts of air pollution on human health are already salient. The World Health Organization (WHO) estimates that air pollution is now the world's largest single environmental health risk, being responsible for one in eight of total global deaths in 2012 (around 7 million deaths globally). According to the Lancet Commission on Pollution and Health, this number has increased to 9 million deaths in 2015. Air pollution is responsible for heart disease and stroke, lung cancer and respiratory diseases inter alia. Apart from health effects, air pollution also negatively affects key ecosystems, like forests or freshwater, and contributes to accelerate climate change. There is now growing awareness that air pollution and climate change are intertwined (EEA, 2016).

Developing Climate Change Mitigation Technologies (CCMTs) is a key challenge to temper the costs associated with climate change and air pollution consequences (Nordhaus, 2007). As one of the main output of innovative activity, patents related to CCMTs have grown extensively over the last decades. For example, according to Veefkind et al. (2012), the amount of patents published worldwide in "clean energy" has been multiplied by a factor of 4 between 1995 and 2008. In comparison, the total amount of patents applied during the same period has only doubled. Understanding the evolution of CCMTs is important in projecting the future impacts and costs of climate change and pollution-related activities. The European Patent Office has developed the Y02/Y04S tagging scheme which purpose is to identify among the existing and new patents and technological classes, innovations contributing to mitigate climate change. With an original focus on patents related to "low-carbon" technologies and clean energy (Veefkind et al. 2012), this scheme was substantially expanded since then and now includes a wide scope of environmentally-friendly technologies (human health protection, waste management, etc.). Our main goal in this project is to investigate the impact of environmental policies implemented to decrease air pollution on innovations activities in general, and CCMTs identified by this new tagging scheme in particular. Air pollution regulation does not always directly target the reduction of greenhouse gases, but innovations that aim at decreasing air pollution are generally related to a large range of climate change mitigation and adaptation technologies and thus should fall under the CCMT classification.

Early studies generally find a positive relationship between environmental policies and innovation (see Lanjouw and Mody, 1996 for an early reference and Popp et al., 2010, for a recent review). However, there are major empirical challenges in determining the causal effect of environmental regulation on innovations. First, it is difficult to find an appropriate measure of environmental regulation (see *infra*). Second, the presence of third factors, including unobserved technology shocks, may influence both regulatory stringency and innovations. A pure reverse causality may also run from innovations to environmental regulations. This is true when relying on aggregate measures of technological change (at the country, or industry level). Two recent publications use micro(firm)-level data. Aghion et al. (2016) focus on 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 show that there is path dependence in the sense that 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. Calel and Dechezleprêtre (2016) also use firm-level data and explore 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) and that this explains only 1% of the overall increase of low-carbon patenting because regulated firms only account for a small share of all patents. Using firm-level data offers several advantages as it allows to identify more specifically policy impacts. On the downside, it probably leads to an underestimation of the effect because the policy may also affect firms that are not directly covered by the regulation. In this research project, we identify the impact of the environmental regulation at the regional level, which seems to be the most appropriate level of analysis.

This project also contributes to the existing research by proposing an original variable that consistently evaluates changes in environmental regulation stringency. We focus on the main regulatory tool to fight air pollution in European Union (EU) Member States: the Ambient Air Quality Directive (AAQD) in 2008 and its ancestor the Air Quality Framework Directive (AQFD) implemented in 1996. The AFQD and AAQD set numerical limits and thresholds for different types of pollutants and force countries to implement environmental measures in case of exceedance. In this research project, we construct an original variable that identifies, for every EU NUTS-2 region and year, exceedance of air quality limit values and reflects tougher environmental regulation. This proxy variable allows to tackle methodological problems pointed out in the literature (see Bagayev and Lochard, 2017). First, it partially solves the simultaneity problem because air quality limit values are the same for all Member States and are based on the WHO guidelines to protect human health. Second, considering the Air Quality regulation allows us to account for the multidimensions of environmental regulation because countries or regions might implement any policy or measure in the case of exceedance of air quality limit values. Third, limit values are legally bindings and plans and measures implemented both at the regional and national level are regularly evaluated.

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

2 Methodology and data

2.1 Empirical strategy

We implement a quasi diff-in-diff setting to test for the effect of environmental measures on innovation at the EU region (NUTS-2) level over the 1999-2015 period. The main assumption to be tested is that by increasing the cost of polluting activity, environmental measures should boost the incentive for environmentally-friendly innovations. Thus, we expect CCMT patenting activity to be disproportionately more affected in regions enforcing additional air pollution regulations. This conditional mechanism allows to implement a quasi diff-in-diff setting to test for the effect of environmental measures on innovation and include a wide range of fixed effects to control for omitted variables. The basic Poisson specification is as follows:

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

where $Patents_{rct}$ is the count of patents in region r applied for a given technological class c at the 4-digit level and year t.[1] $(1-\delta)K_{rct-1}$ is the region's knowledge capital as given by the stock of patents on the previous period depreciated by a rate δ (in logarithm).[2] $RegAQ_{rt}$ is the measure of a region's environmental regulation change

[1] All variables and sources are defined in the Appendix A (Table 9).

[2] Stocks are constructed using the perpetual inventory method with 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 also add a dummy variable to account for observations with a lagged stock of innovations of zero.

due to the exceedance of a given pollutant concentration as imposed by the EU Air Quality Directive (see Section 2.2), and $CCMT_c$ is a dummy variable capturing the class of patents pertaining to the "technologies or applications for mitigation or adaptation against climate change", i.e. the class Y02 (see Section 2.3). In further refinements of our results, we study how regulations related to different pollutants affect different sub-classes of CCMTs. In order to isolate the effect of environmental regulation on CCMTs from its effect on other technology classes, we also include in our model an interaction term between the variable of environmental regulation and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class ($YCOMP_c$, see Section 2.3 and Appendix A for the construction of this variable). γ_{rc} are technological class-region fixed effects, γ_{rt} are region-year fixed effects and γ_{c1t} are class (1 or 4-digit)-year fixed effects.[3] These fixed effects are crucial to control for regional specialisation in innovative activity, regional trends and shocks and technological trends and shocks common to all regions. Finally, ϵ_{rct} is the usual error term.

Equation (1) allows to compare specialisation in CCMTs (CCMTs vs non-CCMTs) of regions that implement additional environmental measures and specialisation of similar regions that don't. The coefficient of interest, α_2, measures any difference between the two after controlling for all major innovation determinants at the regional level that can be therefore attributed to the environmental regulation. We further test the robustness of our results by estimating our model on different sub-samples and by introducing additional control variables varying at the region-class-year (rct) level (see Section 3.2).

[3]The inclusion of the 4-digit class $\times$ year fixed effects (besides the 4-digit class $\times$ region and region $\times$ year fixed effects) for all technological classes is computationally burdensome, because of the size of the matrix to estimate and the lost of degrees of freedom. To overcome this problem, we incorporate in our estimations 4-digit class $\times$ year fixed effects for CCMTs 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 CCMTs (e.g. clean energy) and a negative trend for others (e.g. CCMT in energy intensive industries), independently of whether the region has to implement environmental regulations or not.

Because our dependent variable is a count of patents, we use a Poisson model and a high-dimensional fixed effects procedure extended to non-linear models (see Guimaraes and Portugal, 2010).

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 and force EU countries to implement environmental measures in case of exceedance. Eight pollutants are considered in this Directive: sulphur dioxide (SO2), nitrogen oxides (NOx), lead (Pb), particulates (PM), carbon monoxide (CO), benzene (C6H6), ozone (O3) and fine particulate matter (PM2.5) (see Table 10 in Appendix).[4]

The general principles of the regulation are as follows. 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 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 in order to fall below the limit value. These measures include medium or long-term actions, such as the development of environmentally-friendly innovations, as well as short-run actions (e.g. suspensions or restrictions of polluting

[4]The AAQD merges the preceding Directive, the Air Quality Framework Directive (1996/62/EC) implemented by the EU in 1996 and its three first 'daughter' directives which entered into force in 1999, 2000 and 2002. It also sets a new air quality objective for fine particulate matter (PM2.5) and allows for time extensions for given zones for PM10, NO2 and C6H6. A fourth 'daughter' directive (2004/107/EC) which sets objectives for Arsenic, Cadmium, Nickel and Benzo(a)pyrene is not resumed in the AAQD.

activities contributing to the non-attainment, traffic restrictions) (see also Bagayev and Lochard, 2017 for a detailed description of the regulation).

We expect the AAQD to affect more generally environmentally-friendly innovations and not only innovations targeting one pollutant or another (qui serait capte par CCMT)

We focus here on compliance with limit values for two major pollutants: particulates (PM10) and nitrogen dioxide (NO2) for several reasons. First, they represent the target of most (68%) air quality plans implemented since 2004 (see also EEA, 2018a).[5] Environmental measures focus mainly on NO2 (43% of air quality plans), followed by PM10 (25%). Second, these two pollutants are the ones that are the most reported by monitoring stations (73% of all stations-years over 1999-2015 for NO2 and 62% for PM10). Except for ozone (O3) and sulphur dioxide (SO2) reported respectively by 55% and 53% of stations-years, all other pollutants are reported by less than 30% of stations-years. We do not consider ozone here for two main reasons. First, ozone is a secondary pollutant coming from the reaction of nitrogen dioxides and volatile organic compounds in the presence of sunlight and may happen away from emission sources. Therefore, measures needed in case of exceedance may involve several municipalities, regions or even countries. Second, under the Air Quality Directive, the ozone standard is a 'target value' (and not a 'limit value') and therefore not legally binding (see below and EEA, 2018b). We do not focus on compliance with limit values for SO2 because in recent years, SO2 concentrations are generally well below the limit values in all EU countries.[6] NO2 emissions and Particulates come from various economic sectors. The largest contributor to NO2 emissions is

[5]Under the EU Air Quality Directive, Member States have to report on the plans and measures they implement and these plans and measures are made available by the European Environment Agency under the Air Quality e-Reporting (Air Quality plans, data flow H). Other pollutants represent the target of less than 15% of air quality plans (O3: 11%, PM2.5: 4.8%, BaP: 3.8%, SO2: 2.5%, CO: 2.3%).

[6]For instance, only eleven regions out of 273 (0.4%) from 6 EU countries registered concentrations above the daily limit value for SO2 at least once over the period 2010-2015 (see also EEA, 2017).

road transport (39% in 2015), followed by energy production and distribution (19%), commercial, institutional and households fuel combustion sector (14%), and energy use in industry (12%). PM10 emissions mainly come from commercial, institutional and households fuel combustion sector (42%), followed by industrial processes and product use (17%) and agriculture (15%) (EEA, 2017).

An important characteristic of the AAQD is that these limit values are legally binding, meaning that judicial actions may be undertaken if a Member State fails to comply with the regulation. Moreover, the European Commission oversees the implementation of EU legislation and can launch legal proceedings, including enforcement measures against Member States that do not comply with the AAQD requirements. The European Commission currently pursues infringement proceedings on NO2 and PM10 against respectively 13 and 16 Member States. Most cases are settled before being referred to the European Court of Justice, which means that the Commission considers that Member States' replies are satisfactory or that they comply with the requests.[7] However, for PM10, five countries have been recently referred to the Court of Justice (Hungary, Italy, Romania, Bulgaria and Poland). For these last two countries, the Court has already handed down judgments, considering that they breached the law. For NO2, three countries have been referred to the Court of Justice in 2018 (France, Germany and the United Kingdom). As a robustness check, we will exclude these countries from the sample, considering that these countries have not fully implemented environmental measures in order to comply with the regulation (see Section 3.2).

Measures to encourage or enforce compliance also rely on peer pressure and pressure

[7]The infringement procedure is the following. The Commission addresses a 'Letter of Formal Notice' to the Member State requesting an answer within two months. Depending on the reply, the Commission may decide to address a second letter ('Reasoned Opinion') (once again with a reply within 2 months) and if the Member State does still not comply with the requests, the case may be referred to the Court of Justice. If the country still does not comply with the decision of the Court, the Commission may refer the country back to the Court and in this case proposes financial penalties.

from citizens and environmental organisations because the directive require Member States to inform the public about the assessment and management of air quality. Very recently, the European Environment Agency (EEA) and the European Commision have launched a European Air Quality Index in order to give "citizens an easy way to access information on their local air quality" (Hans Bruyninckx, EEA Executive Director).

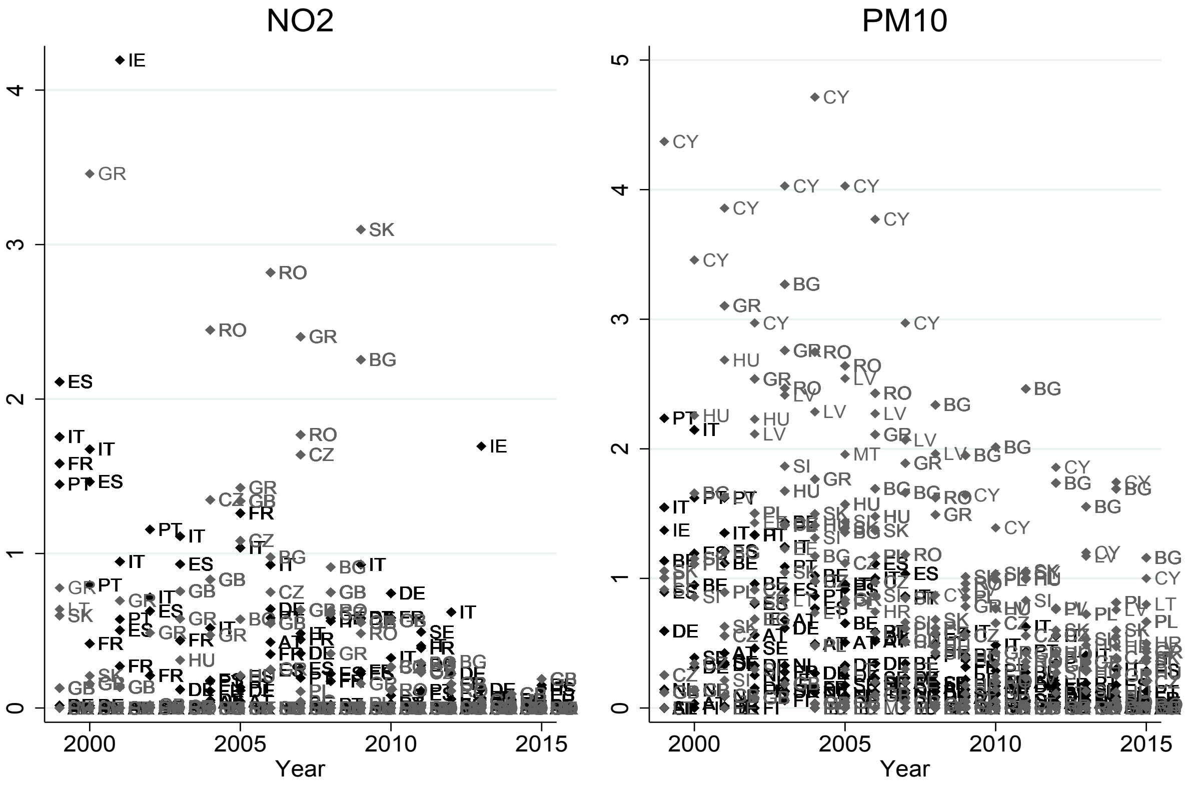
Finally, even if each Member State is responsible for implementing adequate measures in case of exceeding, most environmental measures are implemented at the regional level. Among the 51,530 measures reported for the years 2012 to 2016, 89% are local or regional (and 11% national).[8] Therefore, in our empirical analysis, we consider the regional level as the most appropriate because environmental measures and constraints faced by firms are essentially perceived at this level.

We focus on exceedances of limit values for two main pollutants (NO2 and PM10) as a proxy for change in environmental stringency. More precisely, we construct, for each NUTS-2 region and year, an original variable (RegAQ) that measures, with a dummy variable, exceedances of air quality limit values for each pollutant and zero otherwise (limit values are displayed in Table 10 in Appendix). These variables do not aim to measure the overall level of environmental policy stringency, but rather *additional* environmental measures implemented by EU countries to comply with the AAQD. In our empirical estimations, we also use an alternative variables 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.[9] This variable intends to measure the magnitude of exceedances, which should correlate with the stringency of the regulation.

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

[9]For example, the hourly limit value for NO2 is 200μg/m3 not to be exceeded more than 18 times a year (see Table 10 in Appendix). In 2010, six stations of the Madrid region in Spain have exceeded more than 18 times. 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 ($= (42.88 - 18)/18$).

Figure 1: Intensive regulation (average number of days/times of exceedance over the allowed level) by country and year



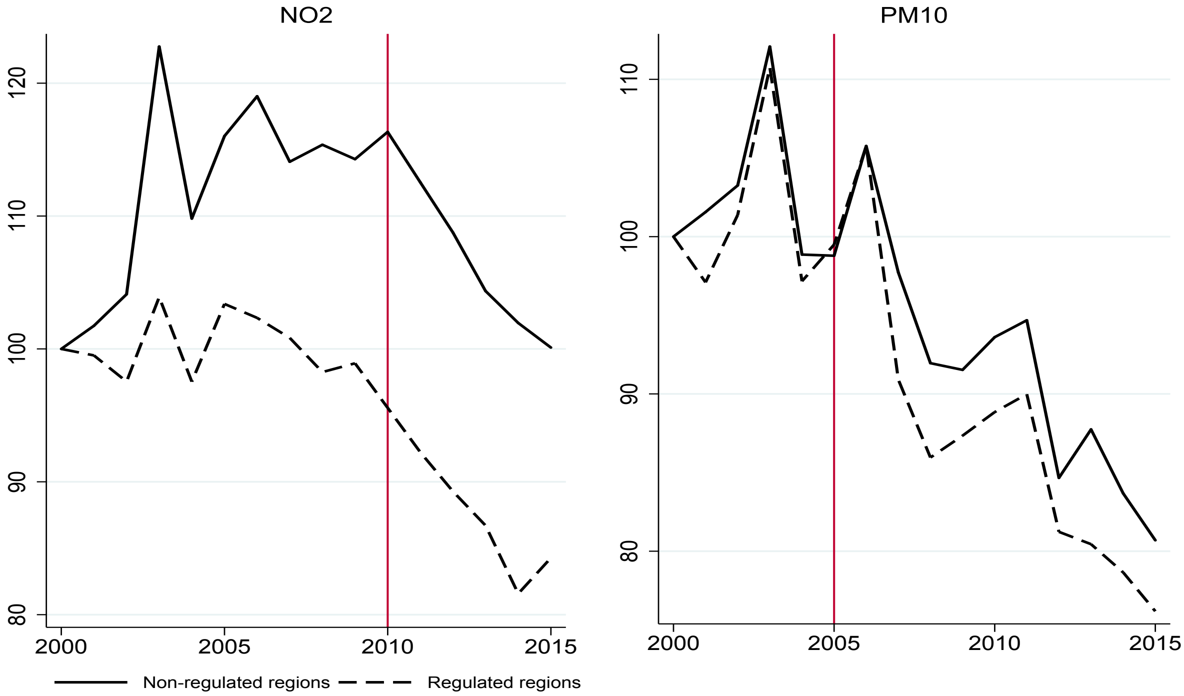
Source: AirBase (EEA) and authors' calculations.

Figure 1 displays the average number of exceedances of limit values over allowed ones by country and year for the two main pollutants (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 allowed ones also decrease over time for the two pollutants.

These proxy variables for environmental regulation have several advantages. They allow 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 governments use many different instruments in order 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 eco-taxation. Indeed, within the AAQD framwork, Member States 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 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 do implement environmental measures in case of exceedances. To provide some indirect evidence that the regulation is enforced sucessfully, we compare the mean indices of annual regional pollutants concentration for 'regulated' regions (i.e. regions that have to implement environmental measures because they exceeded at least once over the period 2000-2015) and 'non-regulated' regions (regions that never exceeded over the same period). Figure 2 shows that the decrease in annual concentration in 'regulated' regions is larger than the decrease in 'non-regulated' regions for NO2 and PM10. Concentrations of NO2 began to decrease in 2010 (date of entry into force of the limit value) and decreased only in regulated regions, as compared to their value in 2000. Concentration trends of PM10 are very similar for regulated and non-regulated regions until 2006 (one year after the entry into force of the limit value) and then began to diverge, with a larger decrease in regulated regions. Overall, this figure provides some evidence that the regulations are enforced successfully.

Figure 2: Mean indices of annual regional pollutants concentration for 'regulated' and 'non-regulated' regions (index 100 in 2000)



Source: AirBase (EEA) and authors' calculations. 'Regulated regions' are defined as regions that exceeded at least once over the period 2000-2015 and 'non-regulated' as regions that never exceeded over the same period.

Last but not least, the AAQD is the most constraining legislation as 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 in 2010.[10] For the two pollutants that we consider here, only NOx appears in both directives. Moreover, most countries have met their national emission ceilings for NOx during the period 2010-2015 and only Austria and Ireland

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

persistently exceeded their respective ceilings. In robustness checks, we will control for potential measures 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, as 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 time of invention, as well as other useful indicators. On the other hand, patents capture only one way for firms, institutions or individuals to protect inventions. Patents' values are also quite heterogenous, where some patents generate high economic rents, while others might remain unexploited at the market place.

Following the recent literature, we proxy innovative change in a given technological 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).[11] Patents are classified using the Cooperative Patent Classification (CPC) scheme. We use annual counts of

[11] 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.

patent applications at 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) in order to ensure that the patents that we consider are of high quality (see e.g. Calel and Dechezleprêtre, 2016).[12]

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 invention, we divide equally 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 period 1999-2015.

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 formalized into algorithms. Thus, it consistently applies to patents filed during our period of investigation (and before). The Y02 category now includes eight different sub-classes and allows for a detailed analysis of the environmental measures that impact on different types of CCMT innovations. The eight sub-classes 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 11 in Appendix A). The class Y04S relates to smart grids. In our empirical analysis, we have all sub-classes except Y02A and Y02D

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

which are too recent for our current dataset. Among the existing categorisations, the Y02/Y04S tagging scheme is the most comprehensive and accurate, and it has been used in several recent papers focusing on clean innovations (e.g. Calel and Dechezleprêtre, 2016).

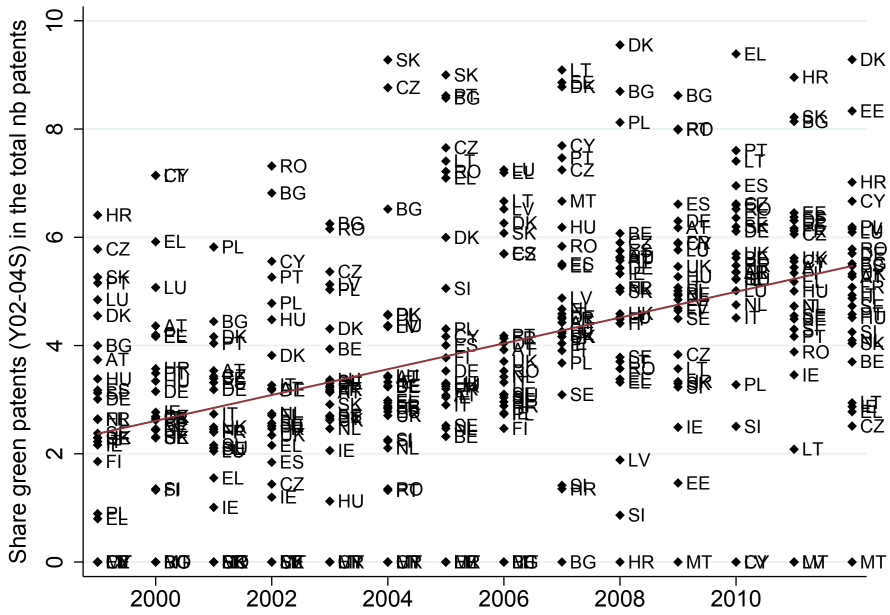
Unlike other CPC classes, the Y02/Y04S scheme has been defined as a purely *complementary* tagging scheme (Veefkind, 2012). In that sense, it comes at the top of the existing CPC classification and does not replace any previously reported CPC class. Patents tagged with one of the CCMT class should thus, by construction, also be assigned to other regular (non-CCMT) CPC classes. To consistently disentangle patents in CCMTs from patents that do not aim at mitigating climate change, any patent tagged with a CCMT class is thus not reported in any other CPC class. This allows to accurately measure the evolution of the number of patents in different CCMTs as compared with the evolution of the number of patents in other, non-CCMT, classes.

Patents relating to climate change mitigation technologies are expanding in many regions. The share of CCMTs in the total number of patents is now about 5% in Europe and it has steadily increased since 1999, in particular for the Y02E sub-class (see Figures 3 and 4). This sub-class (Y02E, clean energy) now represents the largest class in the number of patents, followed by CCMTs in transportation (Y02T) and in production and processing of goods (Y02P) (Figure 4).

The share of CCMTs in the total of patents also varies largely across EU countries, with a larger value than the average in Nordic countries, such as Denmark specialized in wind energy, but also in some Southern or Eastern European countries, such as Greece or Romania specialized in solar energy (Figure 3).

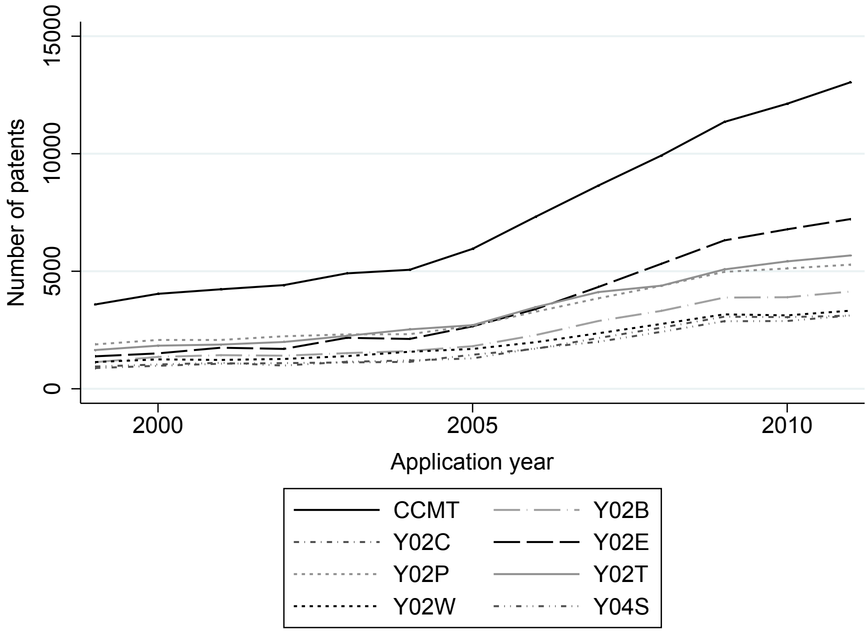
This large variability is also reflected in the share of patents in different CCMTs (Building, Capture, Energy, Industry, Transport, Waste and Smart Grids) in the total number of patents in CCMTs (see Table 1). For instance, Denmark, Greece and

Figure 3: Average share of CCMTs (Y02/Y04S) in the total number of patents by country and year (%)



Source: PATSTAT. The number of patents is computed using fractional counting (see text for details).

Figure 4: Evolution of the number of CCMT patents over the period 1999-2013



Source: PATSTAT. The number of patents is computed using fractional counting (see text for details).

Cyprus are highly specialized in clean energies as compared to other CCMTs, while France, Germany and Sweden are specialized in CCMTs related to transportation. This Table also shows that some Eastern European countries, such as Slovakia, the Czech Republic and Lithuania file relatively more patent applications in CCMTs in waste and wastewater than the average. However, these last numbers should be interpreted with caution because these countries have generally less patent applications (see column 1), so that a small number of patents in one particular sub-class could increase tremendously the share of patents in this sub-class.

At the regional level, this problem is even more pronounced, so that we set at zero the share of regions that have a count of weighted patents lower than 50. The map displayed below (Figure 5) shows that there is also substantial heterogeneity in the average share of patents in CCMTs among EU regions. Most Eastern European regions do not report any patent in CCMTs or have a count of weighted patents lower than 50. Nordic regions, in particular Danish regions and Northern Germany, show the highest share of patents in CCMTs (higher than 5%).

As previously mentioned, the Y02/Y04S scheme is different from other CPC classes as it is an additional tagging scheme next to the regular CPC classification. Because patents relating to CCMTs can be found in many classical (non-CCMT) areas of technology, they do not fall under one single existing CPC class and do not replace any existing class. But, as CCMT tagged patents also relate to the non-CCMT technology classes, we need to acount in our analysis for the complementarity between CCMT and non-CCMT classes.

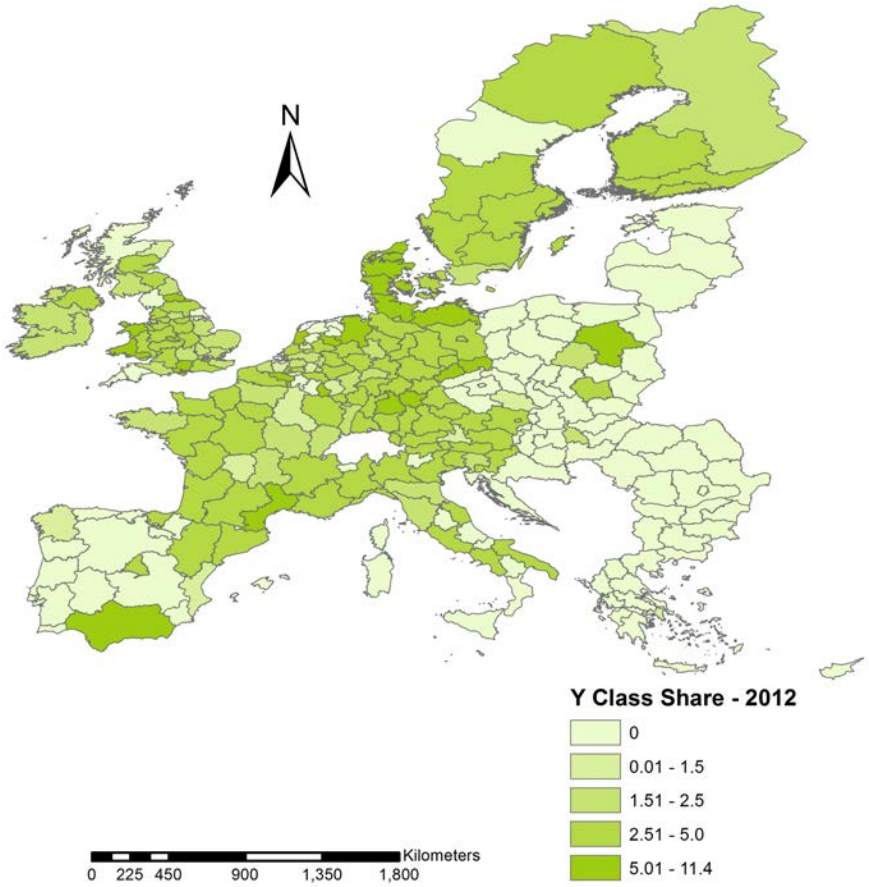
To consistently identify the impact of the environmental regulation on CCMT patents, we therefore also control in our estimations for the intensity of co-occurrences between CCMT and non-CCMT classes ($YCOMP_c$ in equation 1). Not considering for this link in the estimations could bias our coefficients downward, and the extent of the bias could be different across the Y02/Y04S classes.

Table 1: Share of patents in different CCMTs in the total number of patents in CCMTs

Country	Total nb CCMT Pat. (1)	YBuilding (2)	YCapture (3)	YEnergy (4)	YProd (5)	YTransport (6)	YWaste (7)	YSmartGr (8)
Austria	884	19.0	0.9	25.5	22.9	18.7	11.4	1.4
Belgium	796	10.8	0.9	23.3	**36.8**	15.3	11.4	1.5
Bulgaria	13	3.7	0.0	34.7	36.1	21.9	1.3	2.4
Cyprus	5	11.3	0.0	**52.8**	15.5	5.5	11.9	3.0
Czech Republic	75	15.7	0.3	23.4	30.5	7.7	**18.7**	**3.8**
Germany	15,059	10.9	1.4	27.6	22.6	**31.1**	4.7	1.7
Denmark	1,039	10.4	0.9	**56.7**	22.8	4.5	4.0	0.7
Estonia	16	20.1	0.0	47.4	21.7	2.7	8.1	0.0
Greece	44	11.5	0.0	**54.2**	14.5	8.9	10.6	0.2
Spain	658	11.8	0.8	44.3	23.9	10.2	7.9	1.0
Finland	530	29.0	0.4	21.3	27.7	12.5	7.7	1.4
France	3,962	11.8	**2.2**	25.0	19.5	**32.8**	7.1	1.5
Croatia	10	13.8	0.0	21.5	**38.4**	15.0	11.3	0.0
Hungary	70	**30.9**	0.6	12.2	28.1	17.1	11.1	0.1
Ireland	122	**33.9**	0.7	29.9	17.4	3.7	13.2	1.1
Italy	1,634	17.6	1.3	25.7	27.5	17.7	8.5	1.7
Lithuania	6	7.6	0.0	23.3	30.9	8.7	**23.1**	**6.5**
Luxembourg	62	7.9	1.9	18.3	33.9	27.7	10.3	0.0
Latvia	11	3.4	0.0	39.1	**48.9**	0.0	8.6	0.0
Malta	2	25.0	0.0	25.0	25.0	25.0	0.0	0.0
Netherlands	1,426	**30.6**	**3.8**	25.4	28.4	5.8	5.1	0.9
Poland	121	12.1	0.6	22.5	30.4	15.5	15.2	**3.7**
Portugal	48	17.3	**2.3**	25.9	35.4	7.9 1	0.8	0.4
Romania	19	26.3	1.0	42.6	17.1	9.4	3.6	0.0
Sweden	1,077	23.2	0.8	25.2	16.8	**28.4**	3.8	1.7
Slovenia	24	21.7	0.0	29.8	36.6	9.5	1.6	0.8
Slovakia	18	14.6	0.0	36.8	21.0	3.9	**22.8**	0.9
United Kingdom	2,126	17.1	2.1	29.3	20.3	22.4	6.5	2.3
Average	-	16.7	0.8	31.0	26.8	13.9	9.3	1.4

Notes: The total number of patents in CCMTs over the period 1999-2015 (column 1) and the average share of patents in different sub-classes in the total number of patents in CCMTs are computed using fractional counting (see text for details). The three largest shares are marked in bold.

Figure 5: Average share of CCMTs (Y02/Y04S) 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.

To illustrate this, let us consider the example of a firm that develops and patents innovations related to CO2 capture because it is facing new air pollution regulations. Technologies and innovations this firm would develop should thus be related to the Y02C class (*YCapture* dummy) 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 both increase patents in Y02C and B01D classes. In our original patent database about 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 CCMT and non-CCMT classes.[13]

Therefore, we construct a dummy variable ($YCOMP_c$) capturing whether a given non-CCMT class is *complementary* to each Y02/Y04S class using probabilistic co-occurences between technology classes (see Appendix A for details).

3 Evaluating the impact of environmental regulation on innovations in CCMTs

We first present our baseline results, followed by some robustness checks and additional findings.

3.1 Baseline results

In our empirical analysis, we first estimate our baseline equation (eq. 1) using a Poisson estimator on the overall sample including 273 regions, 654 technological

[13]Put differently, this is equivalent to say that due to the interference among groups (among CCMT and non-CCMT 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.

classes and 17 years (1999-2015). To capture a change in environmental regulation we first introduce a dummy variable indicating whether pollutants' concentration exceed the limit value in a given region and a given year (see section 2.2). Estimation results are displayed in Table 2. The interaction between this dummy variable and a dummy variable for CCMTs (the Y02/Y04S class) thus captures the effect of measures implemented to comply with the environmental regulation on the specialisation of regions in CCMTs. In columns (1) and (2) we report the results for PM10 exceedances, and in columns (3) and (4) for NO2 exceedances.[14]

We find that the stock of patents in a given technological class has the expected positive effect and it is significant at the 1% level in all cases. These first results also indicate that regions implementing environmental measures in order to comply with the regulation tend to innovate more in climate change mitigation technologies (columns 1 and 3 of Table 2).

Moreover, when we disaggregate CCMTs into different sub-classes (columns 2 and 4) we obtain stimulating results. Regions that implement additional environmental measures tend to innovate more mainly in energy sources alternative to fossil fuels (YEnergy) and in energy intensive industries (YProd). We also observe increasing green innovations in buildings for PM10 exceedances and in waste and wastewater for NO2 exceedances. This is not totally surprising because the construction of buildings and infrastructure represent a substantial source of PM10 emissions, while NO2 emissions might be caused by waste incineration and wastewater treatment. Overall, it seems that air pollution regulations in EU regions tend to foster innovations in a subset of CCMTs, as compared to non-CCMTs.[15]

[14]In each case, the $RegAQ$ dummy variable measures exceedances of air quality limit values for each pollutant (PM10 concentration averaged over days and years; NO2 concentration averaged over hours and years) and zero otherwise.

[15]Note that our model specification only allows to estimate the impact of environmental regulations on innovations in CCMTs as compared to non-CCMTs. It does not allow to estimate the global effect of environmental regulations on innovations because in this case the $ReqAQ_{rt}$ variable would be collinear with region-year fixed effects.

Table 2: Environmental regulation (dummy) and CCMTs at the region level

	PM10		NO2	
	(1)	(2)	(3)	(4)
$RegAQ_{rt} \times CCMT_c$	0.0369**		0.0571**	
	(0.0185)		(0.0252)	
$RegAQ_{rt}\times$YBuilding		0.124***		0.0896
		(0.0434)		(0.0582)
$RegAQ_{rt}\times$YCapture		-0.0756		0.196
		(0.0994)		(0.151)
$RegAQ_{rt}\times$YEnergy		0.0893***		0.132***
		(0.0300)		(0.0391)
$RegAQ_{rt}\times$YProd		0.0556*		0.136***
		(0.0307)		(0.0456)
$RegAQ_{rt}\times$YTransport		0.0312		0.0554
		(0.0385)		(0.0561)
$RegAQ_{rt}\times$YWaste		0.0814		0.160*
		(0.0560)		(0.0831)
$RegAQ_{rt}\times$YSmartGr		0.0325		0.176
		(0.0932)		(0.142)
$\ln Patents\ Stock_{rct-1}$	0.142***	0.141***	0.137***	0.137***
	(0.00957)	(0.00952)	(0.00953)	(0.00939)
$RegAQ_{rt}\times$YCOMP	0.108***		0.220**	
	(0.0197)		(0.0153)	
$RegAQ_{rt}\times$YCOMP^{Building}		0.0181		0.0261**
		(0.0128)		(0.0126)
$RegAQ_{rt}\times$YCOMP^{Capture}		-0.0304**		-0.0301***
		(0.0122)		(0.0116)
$RegAQ_{rt}\times$YCOMP^{Energy}		0.0298***		0.0636***
		(0.00942)		(0.00914)
$RegAQ_{rt}\times$YCOMP^{Prod}		0.0242***		0.0298***
		(0.00882)		(0.00931)
$RegAQ_{rt}\times$YCOMP^{Transport}		0.00352		00941***
		(0.0119)		(0.0112)
$RegAQ_{rt}\times$YCOMP^{Waste}		0.0225**		0.0606***
		(0.0102)		(0.00906)
$RegAQ_{rt}\times$YCOMP^{SmartGr}		0.111***		0.113***
		(0.0126)		(0.0131)
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 counts of patents per EU region and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

3.2 Robustness analysis

We perform several robustness checks in order to test the sensitivity of our results. In a first step, we use an alternative intensive variable that measures the stringency (the 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. Estimations results, reported in Table 3, provide similar conclusions.[16] Regions implementing environmental measures seem to innovate more in renewable energies (YEnergy) as compared to non-CCMTs (columns 1, 3 and 4). They also seem to innovate more in energy intensive industries (YProd) when we consider exceedance levels above limit values for NO2 (columns 3 and 4). Note that estimation results point to some negative effects of additional measures against PM10 emissions on CCMTs in carbon capture (YCapture) and smart grids (YSmartGr), but these should be considered with caution because the number of patents in these categories is much smaller.

We then estimate our model on several sub-samples to test the robustness of our results with respect to the environmental regulation variable. 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 the regions that exceeded at least once. On our original sample, we have 273 regions. Among these 273 regions, 79 regions from 15 countries never exceeded PM10 limit values. These regions are located mainly in the UK for 44% 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 should provide a sort of 'treatment effect among the treated'. Results are displayed in column (1) of Table 4. They are very close to the baseline estimates (column 2 of Table 2). Similarly, we exclude regions

[16] In this Table we only report coefficients on the main variables but comprehensive estimation results are available upon request.

Table 3: Environmental regulation (exceedance level) and CCMTs at the region level

	PM10 day (1)	PM10 year (2)	NO2 hour (3)	NO2 year (4)
$RegAQ_{rt}\times$YBuilding	0.108**	0.358	0.0181**	0.0417
	(0.0446)	(0.292)	(0.00823)	(0.118)
$RegAQ_{rt}\times$YCapture	-0.350***	-1.805*	0.0412**	0.230
	(0.0782)	(0.800)	(0.0194)	(0.259)
$RegAQ_{rt}\times$YEnergy	0.0960**	0.0563	0.0235***	0.230***
	(0.0422)	(0.271)	(0.00587)	(0.0785)
$RegAQ_{rt}\times$YProd	0.00401	0.246	0.0125**	0.218***
	(0.0324)	(0.195)	(0.00505)	(0.0785)
$RegAQ_{rt}\times$YTransport	-0.0475	0.0394	0.00267	0.0284
	(0.0454)	(0.267)	(0.00495)	(0.0804)
$RegAQ_{rt}\times$YWaste	0.0969**	0.599**	0.0270	0.170
	(0.0446)	(0.274)	(0.0253)	(0.167)
$RegAQ_{rt}\times$YSmartGr	-0.234*	0.482	0.0417***	0.535**
	(0.124)	(0.675)	(0.0156)	(0.252)
$\ln Patents\ Stock_{rct-1}$	0.142***	0.142***	0.142***	0.139***
	(0.00955)	(0.00958)	(0.00958)	(0.00946)
Observations	1,198,944	1,198,944	1,198,944	1,198,944
Control $RegAQ\times$YCOMP	yes	yes	yes	yes
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 counts of patents per EU country and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include, first, interaction terms between the $RegAQ$ variable and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class ($YCOMP$) and, second, a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

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. Other regulations than the AAQD at the EU, national or sub-national 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 estimated coefficient of interest might be biased. There is no objective 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 regulation against pollution, the National Emission Ceilings Directive (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 period post-2010, when the NECD entered into force.[17] 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 sub-sample (column 3 of Table 4) give very 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 do implement environmental measures in case of exceedances. Indirect evidence that the regulation is enforced successfully is that air pollution concentration declines more rapidly in exceeding regions than in non-exceeding regions (see Figure 2). However, one can still argue that some Member States still 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 countries to the European Court of Justice (ECJ) (second to last stage of the procedure). This

[17] 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 a fourth pollutant, fine particulate matter (PM2.5) after 2016.

Table 4: Robustness checks - Regulation (dummy) and CCMTs at the region level

	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)
$RegAQ_{rt}$×YBuilding	0.149***	0.106	0.0110	0.129**	0.224***	0.124***	0.0936
	(0.0473)	(0.0800)	(0.0748)	(0.0442)	(0.0803)	(0.0443)	(0.0589)
$RegAQ_{rt}$×YCapture	-0.0494	0.244	0.541***	-0.119	-0.0201	-0.0324	0.200
	(0.102)	(0.217)	(0.205)	(0.101)	(0.229)	(0.106)	(0.156)
$RegAQ_{rt}$×YEnergy	0.127***	0.272***	0.0932*	0.0961***	0.0610	0.0749**	0.126***
	(0.0324)	(0.0597)	(0.0497)	(0.0307)	(0.0605)	(0.0303)	(0.0388)
$RegAQ_{rt}$×YProd	0.0715**	0.158**	0.253***	0.0751**	-0.00226	0.0558*	0.130***
	(0.0329)	(0.0657)	(0.0610)	(0.0313)	(0.0714)	(0.0327)	(0.0468)
$RegAQ_{rt}$×YTransport	0.0721*	0.133*	0.0517	0.0366	-0.0326	0.0536	0.0653
	(0.0431)	(0.0769)	(0.0704)	(0.0396)	(0.0879)	(0.0402)	(0.0569)
$RegAQ_{rt}$×YWaste	0.109*	0.0223	0.142	0.0682	0.0503	0.0538	0.160*
	(0.0623)	(0.113)	(0.104)	(0.0590)	(0.120)	(0.0604)	(0.0835)
$RegAQ_{rt}$×YSmartGr	0.0768	0.227	0.144	0.0736	-0.0369	0.00826	0.159
	(0.0976)	(0.217)	(0.200)	(0.0957)	(0.187)	(0.0992)	(0.140)
$\ln MeanPol$×YBuilding						0.0892	-0.0165
						(0.127)	(0.0947)
$\ln MeanPol$×YCapture						-0.216	0.0194
						(0.312)	(0.346)
$\ln MeanPol$×YEnergy						0.311***	-0.0288
						(0.120)	(0.0932)
$\ln MeanPol$×YProd						0.168*	0.139*
						(0.0932)	(0.0777)
$\ln MeanPol$×YTransport						-0.243**	-0.0984
						(0.111)	(0.0916)
$\ln MeanPol$×YWaste						-0.106	-0.347**
						(0.157)	(0.112)
$\ln MeanPol$×YSmartGr						0.271	-0.0145
						(0.415)	(0.263)
$\ln Patents\ Stock_{rct-1}$	0.173***	0.169***	0.134***	0.153***	0.0879***	0.116***	0.137***
	(0.0115)	(0.0110)	(0.0102)	(0.0102)	(0.0162)	(0.0105)	(0.00969)
Observations	824,154	876,681	800,384	1,057,913	487,112	1,060,197	1,139,746
Control $RegAQ$×YCOMP	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 counts of patents per EU country and year. Robust standard errors clustered at the region-year in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include, first, interaction terms between the $RegAQ$ variable and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class (YCOMP) and, second, a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

means that the EC and/or the ECJ considers that these countries did not implement sufficient and appropriate measures to reduce pollution. Therefore, as a robustness check, we redo the estimation on sub-samples excluding these eight countries that have been referred to the ECJ for not complying with the AAQD (Bulgaria, Poland, Hungary, Italy, Romania for PM10 and France, Germany and the United Kingdom for NO2). Estimations on these sub-samples reported in columns (4) and (5) show broadly similar results. Regulated regions seem to innovate more in clean energy (YEnergy) (as compared to non-CCMTs) and in energy intensive industries (YProd) to some extent (column 4). Note that estimation results reported in column (5) should be taken with caution because the sub-sample excludes in this case the three major countries (France, Germany, UK) representing almost 60% of all observations.

Last but not least, we control for the existence of potential omitted variables by introducing additional variables in the regression. In columns (6) and (7) of Table 4, 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 CCMTs.[18] 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 pollutants concentration. As in our baseline results, we still find that our interaction variable for environmental regulation remains positive and significant for clean energy and energy intensive industries.

3.3 Dynamic and spatial analysis

In order to investigate further the specialisation of regions in CCMT innovations, we introduce some dynamic and spatial analysis. We first examine whether the envi-

[18]Note that, in this specification, the level of pollutants concentration is captured by region-year fixed effects. For this reason, in this Table, we only add the interaction between the level of emissions and the CCMT dummy variables.

ronmental regulation affects innovation specialisation with delays. We then analyse the geographical extent of the environmental measures' impact on innovations.

Dynamic analysis Innovations might react with delays. To analyse the impact of the environmental regulation overtime, we estimate our model introducing lagged measures of the regulation. Estimation results when using the dummy for the regulation variable are reported in Table 5. Column (1) displays the contemporary effect of the regulation, while columns (2) and (3) report the effects of the regulation on specialisation in innovations in CCMTs after respectively 1 year and 2 years. When comparing contemporary effects and effects after 1 or 2 years for each sub-class, all signs remain the same in the three cases for coefficients that are statistically significant. Therefore, it seems that the effects of the regulation are rather stable overtime. After 1 or 2 years, we find that the regulation mainly affects green innovations in Energy (YEnergy), Industry and agriculture (YProd), and Waste and wastewater (YWaste).

Spatial analysis Innovations might be global and not local. In order to investigate further the geographical pattern of innovations, we first introduce as an additional control variable the stock of patents for a given technology class in other regions of the same country weighted by the geographic distance. Results are displayed in Table 6. The stock of patents in other regions seems to be a major determinant of the specialisation of each region in specific technologies. The coefficient on the variable $lnPatents\ Stock_{-rct-1}$ is highly significant and large (even larger than the effect of the stock of patents of the region that is considered). However, even if we control for this additional determinants of innovation at the regional level, the coefficients on the $RegAQ$ interacted variable remain very similar. We still find an effect on environmental measures mainly on regional specialisation in clean energy (YEnergy) and in CCMTs in industry and agriculture (YProd).

Table 5: Environmental regulation (dummy) and CCMTs at the region level - lagged effects

	PM10			NO2		
	No lag	Lag 1 y	Lag 2 y	No lag	Lag 1 y	Lag 2 y
	$RegAQ_{rt}$	$RegAQ_{rt-1}$	$RegAQ_{rt-2}$	$RegAQ_{rt}$	$RegAQ_{rt-1}$	$RegAQ_{rt-2}$
	(1)	(2)	(3)	(4)	(5)	(6)
$RegAQ \times$YBuilding	0.124***	0.0384	0.0562	0.0896	0.0895	-0.0538
	(0.0434)	(0.0480)	(0.0443)	(0.0582)	(0.0652)	(0.0707)
$RegAQ \times$YCapture	.-0.0756	0.0732	0.100	0.196	-0.161	-0.139
	(0.0994)	(0.108)	(0.114)	(0.151)	(0.180)	(0.184)
$RegAQ \times$YEnergy	0.0893**	0.0691**	0.0777**	0.132***	0.162***	0.111***
	(0.0300)	(0.0301)	(0.0304)	(0.0391)	(0.0433)	(0.0463)
$RegAQ \times$YProd	0.0556*	0.0474	0.0400	0.136***	0.159***	0.207***
	(0.0307)	(0.0320)	(0.0321)	(0.0456)	(0.0515)	(0.0613)
$RegAQ \times$YTransport	0.0312	0.0442	0.0185	0.0554	-0.0581	-0.102
	(0.0385)	(0.0388)	(0.0411)	(0.0561)	(0.0633)	(0.0753)
$RegAQ \times$YWaste	0.0814	-0.0510	-0.0329	0.160*	0.0619	0.175
	(0.0560)	(0.0631)	(0.0648)	(0.0831)	(0.0917)	(0.117)
$RegAQ \times$YSmartGr	0.0325	0.0903	0.222**	0.176	0.137	0.00892
	(0.0932)	(0.0957)	(0.0942)	(0.142)	(0.140)	(0.145)
$\ln Patents\ Stock_{rct-1}$	0.141***	0.108***	0.0731***	0.137***	0.106***	0.0728***
	(0.0165)	(0.0172)	(0.0182)	(0.0164)	(0.0172)	(0.0182)
Observations	1,198,944	1,118,315	1,037,007	1,198,944	1,118,315	1,037,007
Control $RegAQ \times$YCOMP	yes	yes	yes	yes	yes	yes
Region-class FE	yes	yes	yes	yes	yes	yes
Region-year FE	yes	yes	yes	yes	yes	yes
Class-year FE	yes	yes	yes	yes	yes	yes

Notes: The dependent variable is the weighted counts of patents per EU region and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include, first, interaction terms between the $RegAQ$ variable and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class (YCOMP) and, second, a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

Table 6: Environmental regulation (dummy) and CCMTs at the region level - Controlling for regional patent stock

	PM10 (1)	NO2 (2)
$RegAQ_{it}$×YBuilding	0.110**	0.0517
	(0.0439)	(0.0587)
$RegAQ_{it}$×YCapture	-0.00816	0.154
	(0.100)	(0.150)
$RegAQ_{it}$×YEnergy	0.0965***	0.114***
	(0.0304)	(0.0396)
$RegAQ_{it}$×YProd	0.0602*	0.126***
	(0.0309)	(0.0464)
$RegAQ_{it}$×YTransport	0.0302	0.0392
	(0.0401)	(0.0563)
$RegAQ_{it}$×YWaste	0.0659	0.141*
	(0.0561)	(0.0826)
$RegAQ_{it}$×YSmartGr	0.0331	0.146
	(0.0925)	(0.145)
$\ln Patents\ Stock_{rct-1}$	0.0696***	0.0681***
	(0.00910)	(0.00903)
$lnPatents\ Stock_{-rct-1}$	0.389***	0.382***
	(0.00832)	(0.00819)
Observations	1,193,909	1,193,909
Control $RegAQ \times YCOMP$	yes	yes
Region-class FE	yes	yes
Region-year FE	yes	yes
Class-year FE	yes	yes

Notes: The dependent variable is the weighted counts of patents per EU region and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include, first, interaction terms between the *RegAQ* variable and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class (YCOMP) and, second, a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

We also introduce regional spatial dynamics with an additional variable evaluating the regulation of the other regions (q) in the country weighted by the distance between each innovative region and the regulated regions. More precisely, we estimate the following equation:

$$
\begin{aligned}
Patents_{rct} &= exp(\beta_1(1-\delta)K_{rct-1} + \beta_2 RegAQ_{rt} \times CCMT_c \\
&+ \beta_3 \frac{\sum_{q\neq r} RegAQ_{qt} \times (1/Dist_{qr})}{\sum_{q\neq r}(1/Dist_{qr})} \times CCMT_c + \beta_4 RegAQ_{rt} \times YCOMP_c \\
&+ \beta_5 \frac{\sum_{q\neq r} RegAQ_{qt} \times (1/Dist_{qr})}{\sum_{q\neq r}(1/Dist_{qr})} \times YCOMP_c + \gamma_{rc} + \gamma_{c1t} + \gamma_{rt}) + \epsilon_{rct}
\end{aligned}
\quad (2)
$$

In this equation, β_3 measures the specialisation in CCMTs of each innovative region when other regions in the country implement additional environmental measures. The corresponding variable takes values between 0 and 1. It is 0 (resp. 1) when no other (resp. all other) regions of the country exceed the limit value in a given year and thus are forced to implement environmental measures. Its value is closer to 1 when close regions exceed as compared to more distant regions.

Estimation results are displayed in Table 7. The positive effect of the regulation on clean energy (YEnergy) and in industry and agriculture (YProd) are mainly found in the regulated region (columns 1 and 2). Environmental measures in other regions have either no impact on specialisation in CCMTs of a given region (column 2) or a negative impact (column 1). This last result might suggest substitution effects. Some environmental measures might trigger local innovations in CCMTs but at the same time reduce innovations in CCMTs (as compared to non-CCMTs) in proximate regions. Note that when we introduce a similar variable for the regulation in other regions ($RegAQ_{-rt}$) not weighted by the distance, we obtain very similar results (available upon request).

Table 7: Environmental regulation (dummy) and CCMTs at the regional level with spatial anaysis

	PM10 (1)		NO2 (2)	
	Region reg ($RegAQ_{rt}$)	Rest of cty reg ($RegAQ_{-rt}$)	Region reg ($RegAQ_{rt}$)	Rest of cty reg ($RegAQ_{-rt}$)
$RegAQ_{rt}$ or $RegAQ_{-rt}$				
×YBuilding	0.0722	0.293***	0.0893	-0.0634
	(0.0467)	(0.0996)	(0.0667)	(0.0966)
×YCapture	-0.116	0.262	0.0316	0.534**
	(0.103)	(0.270)	(0.162)	(0.234)
×YEnergy	0.0958***	-0.213***	0.108***	0.0122
	(0.0310)	(0.0754)	(0.0458)	(0.0705)
×YProd	0.0620*	-0.161**	0.110**	0.0303
	(0.0754)	(0.0792)	(0.0552)	(0.0822)
×YTransport	0.0298	-0.189*	0.0522	-0.123
	(0.0401)	(0.103)	(0.0631)	(0.100)
×YWaste	0.0671	0.0302	0.137	-0.000854
	(0.0621)	(0.140)	(0.0861)	(0.124)
×YSmartGr	0.0762	-0.692*	0.131	0.0665
	(0.0940)	(0.295)	(0.149)	(0.228)
$\ln Patents\ Stock_{rct-1}$	0.141***		0.137***	
	(0.00953)		(0.00942)	
Observations	1,193,909		1,193,909	
Control $RegAQ$×YCOMP	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 counts of patents per EU region and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include, first, interaction terms between the $RegAQ$ variable and a dummy capturing whether a given non-CCMT class is complementary to each Y02/Y04S class (YCOMP) and, second, a dummy variable to account for observations with a lagged stock of innovations of zero (unreported).

4 Testing for endogeneity

To identify the causal link in our estimations our empirical strategy focuses on the interaction between a technology feature (CCMT vs. non-CCMT) 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 us to control in our estimations 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 a potential endogeneity bias and thus need to fulfil a set of assumptions. The two usual concerns are reverse causality and omitted-variable bias.

There are two main suspects as a source of endogeneity in our baseline estimates. First, regions having a "greener" activity (and greener innovations) could also be less likely to exceed pollution thresholds requiring to implement further environmental regulations. This source of reverse causality should bias our estimates downward.[19] The second concern is the 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-CCMT 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.

[19] Note that our robustness analysis (subsection 3.2), by excluding from the sample regions that have never exceeded air quality limits during our time frame (Columns 1 & 2, Table 3), shed 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 3 due to the within-region yearly variations in green innovation that can in turn influence the probability to exceed pollutant concentration levels.

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

To tackle the endogeneity issue and test for the direction of its bias we utilise 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 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 levels and concentration of air pollution in a region. ERA-Interim data from the European Centre for Medium-Term Weather Forecasting (ECMWF) makes available wind and mixing layer information at 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.

The estimation of our econometric specification through two stage instrumental variable method is made complicated because the second-stage specification is non-linear and includes high dimensional 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 8. It should be noted that there are some notable differences in the estimations of Table 8 as compared to our baseline estimations. First, our first-stage estimations do not allow the inclusion of both region-year and region-class fixed effects due to multicollinearity.[20] Accordingly, we do not use region-class fixed effects but instead rely on country-class fixed effects. Second, the sample size is somehow smaller as compared to our main estimations due to missing geographic coordinates of some monitoring stations. Therefore, as a matter of comparison, we include in Columns (1) and (3) estimates of our baseline equation using the same restricted sample.[21] Finally, note as well that our control function approach does not allow to disaggregate the CCMTs into different sub-classes 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 CCMTs ($RegAQ * YCOMP$).

The coefficients of our main variable of interest in Columns (1) and (3) are very similar to the estimates found in the estimation of our baseline equation in Table 2 (Columns 1 and 3).[22] The stock of patents depicts now a larger coefficient due to the inclusion of the country-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 estimations are presented in Columns (2) and (4), with the first-stage estimates provided at the bottom of Table 8. At 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 to exceed pollutant concentration levels, which seems to avail the use of this instrument in our specifica-

[20]At the difference of the patent variable, the first-stage dependent variable is dichotomous (the interaction between $RegAQ$ and $CCMT$).

[21]The estimation routine drops singletons in order 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).

[22]Contrary to Table 2, estimations of Columns (1) and (3) of Table 8 do not include $RegAQ * YCOMP$. Doing so provides very similar, but slightly larger coefficients. We do not report these estimations, but they are available upon request.

tion. The residuals from the first-stage estimations of the $RegAQ * CCMT$ variable are then included in our baseline estimates. These residuals should capture all the endogenous component of our variable of interest and leave 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 CCMT 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 CCMTs is likely to be underestimated.

Table 8: Environmental regulation (dummy) and CCMTs at the region level - Control function

	PM10		NO2	
	Poisson	2SRI	Poisson	2SRI
	(1)	(2)	(3)	(4)
$RegAQ_{rt} \times CCMT_c$	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:				
$RegAQ_{rt} \times CCMT_c$ (residual)		-0.450***		-0.600***
		(0.158)		(0.200)
	1st Stage Dep. var: $RegAQ_{rt} \times CCMT_c$			
$Ventilation\ Coeff_{rt} \times CCMT_c$		-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 counts of patents per EU region and year. Robust standard errors clustered at the region-year in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a dummy variable to account for observations with a lagged stock of innovations of zero (unreported). The control function approach is applied to the estimations reported in Columns 2 & 4. The exogenous instrument used in the 1st stage is the log of the minimum monthly ventilation coefficient (interacted with the dummy CCMT). The 1st stage dependent variable is respectively the RegAQ dummy (interacted with the dummy CCMT) when a region exceeds the limit values for PM10 concentration (Column 2) and NO2 concentration (Column 4). For details see section 4.

5 Final remarks

Our analysis shows a positive and significant effect of environmental measures on specialisation in CCMTs in general. We also find some differential impacts depending on the type of CCMTs, with a strong and positive effect for innovations in clean energy, in CCMTs in energy intensive industries and, to a lesser extent, in buildings and in waste and wastewater. We do not find any effect of the regulation on CCMTs 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 environmental regulations effectiveness to generate CCMT innovations is central to anticipate the cost of mitigating climate change. It also brings further evidence on the trade-off between 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 additionnal environmental measures implemented to comply with the European regulation. But our environmental regulation variable does not allow to compare the effects of different policy instruments on clean innovations. Moreover, the CCMT tagging scheme does not allow to identify the degree to which CCMTs are 'environmentally-friendly' technologies. Finally, our analysis mainly focuses on the demand side and does not investigate comprehensively the process of generation of innovations, and in particular the cost of innovation in different technological fields.

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Appendix A: Data

Table 9: Data description and sources

Variables	Description and sources
$Patents_{rct}$	Count of patent applications to the EPO in a technological class c, in a NUTS-2 region r of the EU28 country (region of residence of the inventor) and a year t (date of priority). To avoid double counting, applications are divided equally among the regions of the inventors (fractional counting, see text for details). Source: EPO Worldwide Patent Statistical Database (PATSTAT).
$\ln PatentsStocks_{rct-1}$	Stock of patents of region r in technological class c at time $t-1$ (in logarithm). The stock variable is constructed using the perpetual inventory method with knowledge depreciation rate set at 20% and the value of a given patent set to zero after 20 years.
Y, $YBuilding$, $YCapture$...	Cooperative Patent Classification (CPC) sections corresponding to Climate Change Mitigation Technologies (CCMTs) based on the tagging scheme developped by the EPO (Y02/Y04S). This section is decomposed into 7 sub-classes (Y02B, Y02C, Y02E, Y02P, Y02T, Y02W, Y04S) (see Table 11 below).
$RegAQ_{rt}$	Environmental regulation proxy. This variable is a dummy that takes the value 1 if emission concentration for NO2 or PM10 exceed the limit value (more than the number of exceedances allowed each year) in at least one of the stations located in region r (see Table 10). As alternative proxies, we use a variable that measures the level of exceedances (Exc. Level) i.e. average number of days or times of exceedance by region and year over the allowed level. Exceedance data come from the AirBase database (European Environment Agency, EEA).
$\ln MeanPol$	Annual mean concentration of pollution in PM10 and NO2 per region and year. Data come from the AirBase database (European Environment Agency, EEA).
$YCOMP$, $YCOMP^{Building}$, $YCOMP^{Capture}$...	Dummy variables indicating that a given non-CCMT class is *complementary* to the corresponding CCMT class (Y02/04S, Y02B, Y02C, Y02E, Y02P, Y02T, Y02W, Y04S). It equals 1 when a given class is complementary to the corresponding CCMT class and 0 otherwise. Details are provided in Appendix A.

Construction of the YCOMP dummy variable

To construct the $YCOMP_c$ variable we follow the common formulation in the economic geography literature and define the probabilistic co-occurence ϕ_{ij} between each non-CCMT class i and every CCMT class j as:

$$\phi_{ij} = \frac{p_{ij}^{obs}}{p_{ij}^{exp}} \tag{3}$$

where p_{ij}^{obs} and p_{ij}^{exp} are respectively the observed and the expected number of co-occurences between the class i and j; $i, j \in c$. The observed number of co-occurences is given by the total number of times classes i and j are found in the same patent. The expected number of co-occurences is given by: $p_{ij}^{exp} = (\frac{n_i}{N} \times \frac{n_j}{N}) \times N$ with n the number of times a class i or j appears in the patent database and N is the total number of patents in the database.

By construction, $\phi_{ij} \geq 0$ and would equal 1 if raw co-occurence counts are identical to a baseline that reflects the different sizes of classes, given by p_{ij}^{exp}. $\phi_{ij} > 1$ implies that classes i and j co-occur more often in the database than one would find 'by chance', it is the opposite when $\phi_{ij} < 1$. We then define a dummy variable capturing whether a given non-CCMT class i is related to a CCMT class j:

$$related_i^j = \begin{cases} 1 & \text{if } \phi_{ij} > 1 \\ 0 & \text{if } \phi_{ij} \in [0; 1] \end{cases} \tag{4}$$

where $j = \{$Y02/04S, Y02B, Y02C, Y02E, Y02P, Y02T, Y02W, Y04S$\}$.

The $YCOMP_c$ variable is then equal to $related_i^j$ for each non-CCMT class $(c = i)$ and its value is set at zero for each CCMT class.

Table 10: Pollutant limit values as given by the EU Ambient Air Quality Directive

Pollutant	Concentration	Averaging period	Limit value enters into force	Allowed exceedances each year
Sulphur dioxide (SO2)	350 μg/m3	1 hour	1.1.2005	24
	125 μg/m3	24 hours	1.1.2005	3
Nitrogen dioxide (NO2)	200 μg/m3	1 hour	1.1.2010	18
	40 μg/m3	1 year	1.1.2010	None
PM10	50 μg/m3	24 hours	1.1.2005	35
	40 μg/m3	1 year	1.1.2005	None
Lead (Pb)	0.5 μg/m3	1 year	1.1.2005 (or 1.1.2010 in specific cases)	n/a
Carbon monoxide (CO)	10 mg/m3	Max daily 8-h mean	1.1.2005	n/a
Benzene (C6H6)	5 μg/m3	1 year	1.1.2010	n/a
Ozone (O3)	120 μg/m3	Max daily 8-h mean	1.1.2010 (T.V.)	25
PM2.5	25 μg/m3	1 year	1.1.2015 (T.V. 1.1.2010)	

Notes: Lead limit value enters into force in 1.1.2010 in the immediate vicinity of some specific industrial sources. For ozone, target value instead of limit value. For PM2.5, target value 1.1.2010 and limit value after 1.1.2015. The first Daughter Directive (1999/30/EC) introduces limit values for SO2, NO2, PM10 and Pb. The second Daughter Directive (2000/69/EC) introduces limit values for CO and C6H6. The third Daughter Directive (2002/3/EC) establishes target values for O3. The AAQD completes the list of pollutants and imposes a limit value for PM2.5.

Table 11: Climate Change Mitigation Technologies (CCMTs) in the Y02/Y04S scheme

CPC group	Name	Description and Examples
Y02B	Buildings	Use of renewables energy sources in buildings, energy efficient lighting, heating, etc.
Y02C	Capture and storage of greenhouse gases	Capture by biological separation, chemical separation, etc.
Y02E	Production, distribution and transport of energy	Energy sources alternative to fossil fuels (e.g. renewable), efficient transmission and distribution technologies
Y02P	Industry and agriculture	CCMT in production of goods in energy intensive industries (chemical, agriculture, agroindustry, etc.)
Y02T	Transportation	Technologies for making transportation less carbon-intensive (e.g. electric vehicles)
Y02W	Waste and wastewater	Technologies related to waste-water treatment (e.g. biological treatment of water) and solid waste (e.g. recycling and recovery)
Y04S	Smart grids	Remote control of power generators, interoperability of electric and hybrid vehicles, energy trading, etc.

Notes: The Y02 scheme now includes two additional categories Y02A (Adaptation to climate change) and Y02D (ICT aiming at the reduction of own energy use). A majority of Y04S also relate to CCMT. Therefore, patents tagged with the Y04S code are often also coded under other Y02 categories.