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Government R&D and green technology spillovers: the Chernobyl disaster as a natural experiment

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Abstract
Using data on green patents filed at the European Patent Office from 1980 to 1984, this paper investigates the effect of increasing government R&D budget on green technology spillovers. Spillovers are measured with patent forward citations over the period 1981–1988. The level of government R&D budget is instrumented leveraging the unexpected occurrence of the Chernobyl nuclear accident—that exogenously pushed governments to reduce their energy-related R&D budgets—in a difference in differences setting. 2SLS results show that a 10% increase in government R&D increases by some 0.7% the number of citations received by green patents. Although positive and significant, the small magnitude of the estimated elasticity suggests that government R&D takes time to let innovation spillovers from green technologies to materialize with some relevance. Interestingly, increasing government R&D expenditures fosters green technology spillovers across traditional (non-green) fields and enlarges the technological breadth of inventions citing green patents. Overall, I conclude that government R&D fosters green knowledge spillovers, accelerates hybridization processes and favors technological diversification around green technologies. However, these positive effects seem to materialize at a slow pace.

Keywords Government R&D · Green innovation · Technology spillovers · Patent data · Natural experiment

JEL Classification O30 · O31 · O38 · Q55 · Q58

1 Introduction

The design of public policies for pursuing environmentally sustainable growth is a top item in the global policy agenda. To necessarily and timely abate CO_2 emissions and concentration in the atmosphere, only two interrelated options seem to be viable: one is to timely develop cost-effective technologies for capturing carbon from the air and storing it safely; the other is to drastically reduce the consumption of fossil fuels. Both options make the

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object of systematic policy interventions, requiring long-term systemic vision and strong coordination between institutions (Covert et al., 2016).

Innovation plays a key role. Due to the so-called 'double-externality' problem affecting green innovation (Rennings, 2000), combining *technology-push* with *demand-pull* policies is decisive. Literature investigating the link between policies and green innovation has indeed flourished during the last decades and empirical evidence have extensively demonstrated the positive effect of several policy tools on the generation and diffusion of green technologies (GTs).[1]

More recent studies have focused on technological knowledge spillovers from GTs, providing promising evidence. The motivation of investigating technological spillovers from GTs is straightforward: if GTs generate larger spillovers than traditional emitting technologies, the necessary policy intervention to support green R&D would lead to beneficial effects on economic growth, also in the short term. In other words, if spillovers from GTs are not narrower than spillovers from other innovation activities, shifting public R&D towards GTs would lead to a win-win combination: addressing environmental issues while guaranteeing sustained economic growth. This emerging literature suggests that GTs actually show general purpose content and their impact in terms of technological spillovers is larger than the average impact of other technologies (Popp & Newell, 2012; Cecere et al., 2014; Dechezleprêtre et al., 2017; Barbieri et al., 2020).

Therefore, investigating whether specific policy tools enhance spillovers from GTs represents a relevant step in advancing our understanding of the economics of green technical change. Among the policy tools at hand, public R&D is surely one of the most important.

The positive link between public R&D and technological knowledge spillovers is indeed well documented (e.g. Jaffe, 1989, Jaffe & Trajtenberg, 1996, Trajtenberg et al., 1997, Bacchiocchi & Montobbio, 2009). However, studies that systematically focus at the role of public R&D for spillovers generated by GTs are limited and not conclusive. Few exceptions are in the field of renewable energy (e.g. Popp, 2016, 2017), reporting mainly positive results.

The present study aims at enriching this strand of literature, providing causal evidence of the positive effect of public R&D on technological spillovers generated by GTs. Precisely, in this paper I test three main hypotheses on the expected positive effect of increasing public R&D on (i) overall technological spillovers from GTs, (ii) the technological breadth of these spillovers, and (iii) the spread of green technological knowledge also into more traditional, non-green technological fields.

To test these hypotheses, I use data on green patents filed at the European Patent Office from 1980 to 1984—together with their citation patterns observed over the period 1981–1988. Because it is reasonable to consider government decisions about the level of R&D budget to be endogenous with respect to knowledge generation and spillovers, I leverage the unexpected occurrence of the Chernobyl nuclear accident (April 1986)—an exogenous shock affecting government R&D spending in energy-related technologies—to instrument the level of government R&D. I show in Sect. 4 that there was no pre-trend in government R&D budget across sectors before 1986, and that the Chernobyl nuclear

[1] Among all, see: Green et al. (1994), Jaffe and Stavins (1995), Porter and van der Linde (1995), Lanjouw and Mody (1996), Jaffe and Palmer (1997), Kemp (1997), Rennings (2000), Jaffe et al. (2002), Popp (2002), Brunnermeier and Cohen (2003), Popp (2003), Beise and Rennings (2005), Jaffe et al. (2005), Popp (2006), Frondel et al. (2007), Frondel et al. (2008), Crabb and Johnson (2010), Johnstone et al. (2010), Popp et al. (2010), Renning and Rammer (2011), Costantini and Mazzanti (2012), Horbach et al. (2012), Costantini and Crespi (2013), Ghisetti and Quatraro (2013), Costantini et al. (2017) and Orsatti et al. (2020a).

accident indeed affected only the level of government R&D related to energy generation in 1986 and in the years immediately after, negatively. This allows me to instrument the level of government R&D in a difference in differences setting in the first stage of a 2SLS model and, therefore, to estimate the causal effect of increasing government R&D budget on GT spillovers.

Results show that increasing the level of government R&D budget fosters overall technological knowledge spillovers generated by GTs. In particular, a 10% increase in public R&D significantly increases the number of citations to green patents by some 0.7%. An immediate implication is that government R&D would be a lever to ensure sustained growth in the short-term while shifting resources towards green innovation. Moreover, increasing government R&D has positive effects on both the average technological distance of patents citing GTs and on the number of citations GTs receive from non-green patents. Overall, this suggests that government R&D enlarges the breadth of technological spillovers from GTs—fostering technological diversification—and accelerates the hybridization of traditional production methods.

However, the relatively small magnitude of the estimated coefficients suggests that government R&D takes time to let innovation spillovers from GTs to materialize with some relevance. Unfortunately, no previous studies using patent data provide direct, extensive evidence (and, therefore, some sort of benchmark) of the link between public R&D and technological spillovers from GTs. Based on scientific publications, the evidence reported by Popp (2016) is somehow an exception. By combining data on scientific publications for alternative energy technologies (biofuels, energy efficiency, solar energy and wind energy) with data on government R&D support, Popp (2016) finds that US$1 million in additional government funding leads to one to two additional publications, but with lags as long as ten years between initial funding and publication. He also estimates large lags in terms of patents citing these publications. This evidence confirms that government R&D is a lever for scientific advances with technological impact. Yet, the realization of these advances may take long time to materialize. The results of the present study go in a similar direction, suggesting that government R&D fosters technological knowledge spillovers from GTs, but at a slow pace.

The rest of the paper is organized as follows. Section 2 reviews the background literature and proposes three working hypotheses. Section 3 describes the research design, the identification strategy, the data collection, the variables used and the empirical models applied. Section 4 presents and discusses the results. Section 5 concludes.

2 Theoretical background and hypotheses

The so-called double externality problem hampers investments in green innovation (Rennings, 2000). The causes are well known. First, non-appropriability and non-exclusivity of technological knowledge are the two main features behind externalities—common to any kind of innovation—that lead to market inefficiencies when referring to R&D investments. Second, GTs bring about local and global benefits in terms of environmental protection—a positive externality for society (Jaffe et al., 2002). This double externality exacerbates the traditional uncertainty of R&D activities. Public policy interventions designed to necessarely boost green R&D investments are therefore systematically required (del Río González, 2009; Mowery et al., 2010).

The portfolio of available mechanisms is wide and encompasses heterogeneous demand- and supply-oriented policy tools (Johnstone et al., 2012). From the supply-side, government R&D is key. Studies in the field of energy indeed confirm the positive link between public R&D and the generation and diffusion of GTs (e.g. Klaassen et al., 2005, SagaR& van der Zwaan, 2006, Bointner, 2014). Other papers—focusing directly on the linkages between university, research centers and industry for the generation of GTs—provide further confirmatory evidence of that positive relationship. Cainelli et al. (2012) show that more radical and relatively new innovations such as environmental ones are more likely to be generated in contexts of networking and cooperation with universities. Similarly, De Marchi and Grandinetti (2013), comparing environmental with standard innovation, show that the former more promptly responds to collaborations with universities and research centers than the latter. Triguero et al. (2013) find that small and medium firms interacting with institutional agents (i.e. research institutes, agencies and universities) are more productive in green patenting activities. Fabrizi et al. (2019) argue that universities and public research centers contribute in green research networks more than private firms. Quatraro and Scandura (2019) show that the involvement of academic inventors in patenting activity bear positive direct effects on the generation of GTs. They also find a positive effect on GTs of local spillovers from non-green technological domains and, interestingly, that academic inventors compensate for local scarcity of spillovers from non-green technological areas.

However, shifting public R&D towards green innovation does not hamper short-term growth only if GTs generate, on average, at least the same level of innovation spillovers generated by other technologies. Understanding innovation spillovers from GTs has therefore strong policy implications. Recent studies on innovation spillovers from GTs provide optimistic evidence. Popp and Newell (2012) find that patents in sustainable energy fields receive more citations than other patents, and that their forward citations stem from a variety of other technological domains. Cecere et al. (2014) focus on GTs based on ICTs or software applications (e.g. ICTs for renewable energy and sustainable mobility). They show that green ICTs rely on a wide variety of knowledge sources and actors, and that they have high pervasiveness. Dechezleprêtre et al. (2017) compare innovation spillovers between clean, dirty and other emerging technologies using patent citation data. They focus on two sectors, electricity and transport, and find up to 40% higher levels of spillovers from clean technologies. They also use firm-level financial data to investigate the impact of knowledge spillovers on firms' market value and find that the marginal economic value of spillovers from clean technologies is also greater. In a similar vein, Barbieri et al. (2020) extensively use patent data to explore the knowledge recombination processes leading to GTs and their impact in terms of knowledge spillovers. They find that GTs are more complex and appear to be more novel than the average. Importantly, they find larger and more pervasive spillovers from green patents than from other patents.

The peculiarities of combinatorial innovation processes behind GTs might explain why they likely generate large spillovers. More than many other innovations, GTs require, in fact, combinatorial processes conducted across different and loosely related areas of the knowledge landscape (Zeppini & van den Bergh, 2011; Renning & Rammer, 2009; Nemet, 2012; Horbach et al., 2013; Benson & Magee, 2014). GTs also show higher complexity and novelty than the average (Quatraro & Scandura, 2019; Barbieri et al., 2020), systemic nature, general purpose content, rely considerably on external knowledge (Ghisetti et al., 2015), and more likely originate from inventive activities performed by experienced teams, better able to creatively recombine extant technological knowledge (Orsatti et al., 2020b).

A relevant feature that the literature on green technical change undervalued so far is whether specific policy schemes and tools, e.g. government R&D, spur not just the generation and the diffusion of GTs, but also their innovation spillovers potential. Few exceptions are in the field of alternative energy. Popp (2016) combines data on scientific publications for alternative energy technologies (biofuels, energy efficiency, solar energy and wind energy) with data on government R&D support and provides information on the lags between research funding and new publications. Moreover, he links the latter also to citations in US energy patents. He finds that US$1 million in additional government funding leads to one to two additional publications, but with lags as long as ten years between initial funding and publication. He also estimates large lags in terms of patents citing these publications, concluding that the realization of scientific advances may take long time to materialize in innovation forms. Largely based on Popp (2016), Popp (2017)—using data on both scientific articles and patents pertaining to three alternative energy technologies (biofuels, solar and wind energy)—finds that scientific articles most highly cited by other scientific articles are also more likely to be cited by future patents. Moreveor, he finds that research performed at government institutions appears to play an important translational role linking basic and applied research, as government articles are more likely to be cited by patents than any other institution, including universities.

The claim that public R&D leads to relevant innovation spillovers is based on the idea that public institutions produce and disseminate key scientific knowledge for subsequent, more applied research (Foray and Lissoni, 2010). The evidence that this is actually the case is vast. The pioneering contribution by Jaffe (1989) shows that the number of corporate patents is positively affected by R&D performed by local universities. Jaffe and Trajtenberg (1996) compare university with corporate patents, finding that the former were cited more frequently than the latter. Similarly, Trajtenberg et al. (1997) find that university patents receive more citations than other patents, concluding that they are more important. At the same time, they also stress that university patents make fewer backward citations to previous research, suggesting that they are also more basic. Bacchiocchi and Montobbio (2009) conduct a similar analysis in a multi-country setting. They find that university and public research patents receive on average more forward citations than other patents. However, this is mainly driven by US universities.

Several contributions stressed the importance of geographical proximity with research performed by universities and public institutions for firm innovation (e.g. (Jaffe, 1989; Belenzon & Schankerman, 2013)). Geographical proximity to universities and public research institutes matters for firm R&D due to the intrinsic tacitness of scientific knowledge produced, to the importance of face-to-face interactions between private and public actors, and to the fact that firms need also non-specific knowledge spillovers from public contexts to successfully perform R&D activities (Koch & Simmler, 2020).

Another related strand of literature pointed to the peculiarities of the educational endowment and skills of academic inventors to explain heterogeneous and boundary-spanning innovation outcomes performed in academic contexts. When looking at successful teamwork-knowledge-production, in fact, scholars stressed that the educational background of inventors is one of the most important driver, particularly in science or engineering (Allen, 1984). Indeed, inventors with higher educational attainment (typically academics) are more likely to better individuate and solve technological problems, less likely to be locked-in by cognitive constraints, more prone to engage in boundary-spanning innovation activities (e.g. (Walsh, 1995; Pelled, 1996)). Gruber et al. (2013), for example, find that scientists, more than engineers, produce patents spanning multiple technological boundaries, suggesting that a strong scientific background is key in managing knowledge recombination across different, not necessarily related, domains.

Given the peculiarities of innovation processes leading to the generation of GTs and the uniqueness of R&D conducted at the public level, we can propose the following working hypotheses:

H1: *Increasing government R&D fosters technological spillovers from GTs.*
H2: *Increasing government R&D favors technological spillovers from GTs that benefit also traditional, non-green innovation processes.*
H3: *Increasing government R&D enlarges the technological breadth of spillovers from GTs.*

3 Empirical methods

3.1 Data and sample

I study the relationship between government R&D budget and innovation spillovers from GTs exploiting information contained in patent citation data. Precisely, I select green patents applied at the European Patent Office (EPO) between 1980 and 1984 by inventors residing in 16 OECD countries.[2] Patents are classified as green according to two established international classifications, both based on the International Patent Classification (IPC): The WIPO "IPC Green Inventory" that identifies patents related to the so-called "Environmentally Sound Technologies" and scatters them into their technology fields,[3] and the OECD Indicator of Environmental Technologies, which features seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting.[4] I combine both classifications to individuate green patents, removing nuclear power-related patents that do not enter the analysis.

The resulting sample consists of 16,091 unique green patents. Of them, 1,631 are in the energy field (10.14%). Patent citations have been collected for the period 1981–1988 included.[5]

[2] Australia, Austria, Belgium, Canada, Switzerland, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the UK and the US.

[3] See https://www.wipo.int/classifications/ipc/en/green_inventory/.

[4] See https://www.oecd.org/env/indicators-modelling-outlooks/green-patents.htm.

[5] I stop the analysis in 1988 due to the events occurred in the former USSR territories and in Germany in the late 1980s that might be a confounding factor for the present study.

3.2 Variables

3.2.1 Dependent variables

I measure technological knowledge spillovers through the number of citations received by green patents. The number of citations a patent receives is a signal that the knowledge embedded in the protected technology is somehow used later in further technological advances (Trajtenberg, 1990). Indeed, since citations show the degree of novelty and inventive steps of the patent claims, they identify the antecedents upon which the invention stands. Therefore, a citation from patent A to patent B indicates that part of the knowledge protected by patent B is also used in generating the technology protected by patent A. Citations thus capture the technological impact of an invention: the more a patent is cited the more the protected technological content is used in further innovation processes. Due to this reason, citations are a good proxy for innovation spillovers.[6] Citations are corrected for DOCDB patent families to account for the entire flow of citations received by each patent.[7]

To test the second and the third hypotheses, I estimate the effect of a change in the level of government R&D on, alternatively: *a)* the number of citations from non-green patents; and *b)* the average technological distance of the citing patents.

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

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

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

To measure the technological distance between citing patents and the focal green (cited) patents, I calculate $d(i, j)$ for all IPC pairs formed by citing IPC classes and IPC classes contained in the focal patents. For each focal patent i at time t, the dependent variable is then the average technological distance from its citing patents.[8]

[6] As stressed by Jaffe and de Rassenfosse (2017), "(c)*itations are, first and foremost, an indicator of technological impact*" [p. 12]. Due to the richness of information contained in patent documents, citations are largely used in the literature to track knowledge flows (Jaffe et al., 1993; Jaffe & Trajtenberg, 1999; Maurseth & Verspagen, 2002; Bottazzi & Peri, 2003; Bacchiocchi & Montobbio, 2010). Griliches (1990) and Breschi et al. (2005) provide a path-breaking and renowned survey. For a recent survey about the use of patent citation data in social science research, see Jaffe and de Rassenfosse (2017).

[7] Patent families essentially originate from a company or an inventor applying for the protection of the same invention at different patent offices. This results in a series of equivalent filings that patent examiners and attorneys can cite indifferently. Simple patent families are quite restrictive sets of equivalents, all sharing the same priority (an original filing at one or another patent once, before extension elsewhere). DOCDB are an alternative of simple families. For a complete discussion about the opportunity of correcting citations for patent families, see Martınez (2011).

[8] To build the measure of technological distance I consider all EPO patents filed during 1980–1988 that cited at least another EPO patent.

3.2.2 Independent variable and controls

The main independent variable is the yearly level of *Government appropriation or outlays budget for R&D* (GBAORD) by socio economic objective (SEO).

GBAORD is a budget-based data, which allows government support for R&D to be measured. It is the result of a joint OECD-Eurostat international data collection on resources devoted to R&D. This involves identifying all budget items with an R&D component and measuring or estimating their R&D content in terms of funding. These estimates are less accurate than performance-based data but, as they are derived from the budget, they can be linked to policy through classification by "objectives" or "goals".

GBAORD series cover R&D in exploration and exploitation of the earth, environment, exploration and exploitation of space, transport, telecommunication and other infrastructures, energy, industrial production and technology, health, agriculture, education, culture, recreation, religion and mass media, political and social systems, structures and processes, general advancement of knowledge, defense.[9] They include R&D performed on the national territory as well as payments to foreign performers, including international organizations. GBAORD, however, covers only R&D funded by central government; local government and, sometimes, also provincial government are excluded.

To assign GBAORD to patents I follow two steps. First, I assign SEOs to economic sectors (NACE rev. 2 sectors) following the method proposed by Stančìk (2012). Second, I assign NACE codes to IPC classes following the method proposed by Van Looy et al. (2014). This two-step matching procedure allows to measure the level of GBAORD for each technology in which the patents have been classified, differentiating between energy and non-energy domains. It is worth noticing that, unfortunately, I cannot measure the exact level of government R&D funding assigned to the green sub-category for each observed field. Therefore, I can only estimate the effect of changes of aggregate government R&D budget. Under the assumption that the composition of the funding—green *vis-à-vis* non-green—was stable over time across technological domains during the period considered, changes in the overall level of R&D allows us to capture variability in terms of public (green) R&D intervention across domains.[10]

Control variables include a binary variable for energy patents[11] and a post-Chernobyl-accident time variable. The interaction between the two will be used as the instrumental variable for the level of GBAORD. Moreover, I also include additional time-varying controls. First, I include the (log transformed) amount of total intramural business R&D expenditures (*BERD*), as a control for the overall private innovation effort at the country level. Second, I include a measure of emission intensity at the country level to control for the overall environmental policy effort that is expected to indirectly foster innovation in GTs.[12]

[9] A complete description of SEOs is provided by the Frascati Manual 2015 (OECD), chapter 12.4.

[10] Sector-specific GBAORD is measured at the country level (i.e. in the analysis, the variability over time of GBAORD is therefore country-sector specific). Patents are assigned to countries according to the inventor's country of residence, as commonly done in extant studies.

[11] The coefficient of the binary variable for energy patents is dropped because of the inclusion of patent fixed effects in the preferred specifications.

[12] This measure comes from the World Bank database (2017) and is expressed as ten kg per 2010 US$ of GDP. It is assigned to the focal patent according to the inventors' country of residence. Unfortunately, the World Bank database does not provide data on emission intensity for Germany before 1991. I therefore

Both *BERD* and *Emission intensity* are assigned to patents according to the inventor's address of residence.[13] Moreover, I also add the (log transformed) level of oil price, adjusted for inflation, to control for possible shocks in the oil and gas industry affecting both innovation in renewable energy (Pegram, 1991) and the volatility of public energy R&D expenditures (Baccini & Urpelainen, 2012). All models include also patent and year fixed effects. Table 1 provides summary statistics of the variables used.[14]

3.3 Empirical design

3.3.1 Identification strategy

The relationship between government R&D budget and technological spillovers from GTs is likely endogenous due to both omitted variable bias and reverse causality. About the former issue, for example, R&D policies and firm innovation are simultaneously affected by the quality of the local institutional context and by human capital features, which are hard to measure appropriately. About the second issue, the stock of deployed technologies, together with their levels of spillovers, drive the design of innovation-oriented polices. Thus, technology pulls policy intervention through several channels.

To overcome these endogeneity issues, I leverage the unexpected occurrence of the Chernobyl nuclear accident in 1986 as an exogenous shock affecting government R&D budget related to energy. The 1986 Chernobyl nuclear accident is classified as "Level 7: Major accidents" by the International Nuclear and Radiological Event Scale (INES), and is considered—together with the 2011 Fukushima Daiichi disaster—as the most relevant nuclear accident ever occurred. The effects of the Chernobyl accident prompted strong international debates about the security of the entire energy generation system, calling for immediate policy responses worldwide. As a matter of fact, several European countries adopted rigid policy interventions against nuclear power investments, immediately after the Chernobyl event. Finland shelved the application on its fifth nuclear power station and decided not to expand its nuclear program. Similarly, the Netherlands congested its nuclear power program and Austria decided not to start any investment in nuclear power generation, even if the construction of its first reactor was already completed at that time. Italy

Footnote 12 (continued)

exclude patents invented in Germany from the main analysis. However, in a robustness check I consider also those patents, omitting emission intensity from the control variables. Results are consistent with the main analysis and are reported in Table 6. Alternatively I include the Government budget for R&D directly related to the environment as a control for the overall country environmental policy effort. Following the Frascati Manual 2015 (OECD), the SEO "Environment" covers R&D aimed at improving the control of pollution, including the identification and analysis of the sources of pollution and their causes, and all pollutants, including their dispersal in the environment and the effects on humans, species (fauna, flora, microorganisms) and the biosphere. This SEO seems not to be directly related to specific green technologies. It instead more generally targets basic research for environmental issues, possibly spreading on the overall environmental research spectrum. I thus use this kind of expenditure as a further control for the overall public policy pressure. However, since I can not rule out the possibility that this kind of R&D targets specific GTs, I use this measure only in robustness analyses. Results do not change when it is included and are reported in Table 6.

[13] Fractional count in the cases of multiple inventors residing in different countries filing the patent.

[14] Patent data are from the CRIOS database (Coffano and Tarasconi, 2014) Data about GBAORD and BERD are from the OECD.Stat database (2010 million US Dollars, PPP). Data about emission intensity are from World Bank. Oil prices have been extracted from the IEA energy statistics database (2010 US Dollars, adjusted for inflation).

was one of the countries that replied to the accident more vigorously: after the outcome of the national *referendum* held in 1987 to stop local nuclear energy production activities, the Italian government immediately shut down all nuclear power plants operating in the country.

The fall of nuclear power due to the Chernobyl accident meant the fall of public R&D investments in all energy sources alternative to fossil fuel. Preliminary descriptive evidence corroborates this. Figure 1 plots the pattern of the average government spending for R&D comparing energy and industrial production in selected EU countries (i.e., Austria, Belgium, Denmark, France, Germany, Greece, Ireland Italy, the Netherlands, Norway, Spain and Sweden) between 1982 and 1990. While the two trends show no significant differences over the period 1982–1985, a clear gap has opened up since 1986, with energy-related spending falling visibly and government R&D for other industrial production projects continuing to steadily increase.[15] The paper "Appendix" provides more descriptive evidence pointing to the negative consequences of the Chernobyl shock on alternative energy related public R&D.

The occurrence of the Chernobyl accident provide, therefore, a suitable setting to investigate the causal effect of changes in government R&D budget on technological spillovers from green patents. Indeed, we can exploit variation across time (i.e. before and after the Chernobyl accident) and technological fields (i.e. energy *vis-à-vis* non-energy) to instrument the level of government R&D. The time at which government R&D is funded (before or after the Chernobyl nuclear accident) as well as the technological domain it targets (energy versus other technological domains) determine the likelihood that the patent is affected by the Chernobyl accident. The identification strategy relies on the fact that only the level of government R&D in the energy domain was affected by the Chernobyl accident. The level of government R&D in the energy domain before the Chernobyl event and the level of government R&D in other domains before and after the Chernobyl event were not affected. Therefore, I can combine differences in government R&D within different technological domains (energy vs. non-energy) with differences across cohorts induced by the shock (pre-Chernobyl vs. post-Chernobyl). After controlling for the energy field and the cohort effect (post-Chernobyl), the interaction between the two can be used as an exogenous variable capturing the causal effect of the Chernobyl accident, which, in turn, can be used as an instrument for the level of government R&D.

If the Chernobyl accident exogenously forced governments to reduce R&D funding for alternative to fossil fuel technologies, the interaction between the dummy signaling for the energy domain and the post-Chernobyl indicator should have a negative and significant effect on the level of government R&D budget, while controlling for energy field and cohort effects. This difference-in-differences (DiD) specification controls for overall time trends in government R&D (across all green technologies) and for time invariant unobserved differences between technological fields (Angrist & Pischke, 2008).

The DiD can be interpreted as the causal effect of the Chernobyl accident under the assumption that, in the absence of the Chernobyl shock, the pattern of government R&D

[15] Dooley (1998) found that most IEA member states reduced public energy R&D expenditures from the mid-1980s to the 1990s. He argues that this decrease is mainly due to deregulation of the energy markets, and that the remaining R&D money was shifted towards short-term, less risky research projects. Wiesenthal et al. (2012) provide a similar justification to this decrease, arguing that it was partly determined by the liberalization and privatization of the energy sector. However, a tremendous drop is evident in the second half of the 1980s (on average, -57% from 1985 to 1990) for selected EU countries that, notably, did not follow a comparable pattern as the UK and the US in terms of liberalization and privatization of the energy sector at that time.

would not have been systematically different between energy and non-energy green domains. Descriptive evidence reported in Fig. 1 already suggests that this was the case. However, to provide robust evidence of the validity of this assumption for the sample of interest, I formally test for the absence of pre-trends in the level of government R&D budget across technology fields, as described in the next Section and discussed in Sect. 4.1.

3.3.2 Empirical models

To estimate the effect of GBAORD on citations received by green patents, I propose three specifications of a two-stage least square model (2SLS).

In the first stage (which is common to all three specifications), I estimate the level of GBAORD with a linear probability model in the DiD configuration described in the previous section. Precisely, I include the following variables in the DiD model: the interaction between the energy domain dummy and the post-1986 indicator ($ENERGY_i \times POST_{i,t}$, whose effect is captured by the coefficient β_2 in equation 2), which captures the causal effect of the shock due to the Chernobyl nuclear accident on GBAORD for energy patents; the post-Chernobyl period indicator ($POST_{i,t}$), which takes value 1 for both energy and non-energy patents from 1986 to 1988; patent and year fixed effects (α_i and δ_t, respectively); and the set of time-varying control variables described in Sect. 3.2.2 ($\boldsymbol{\Omega}'_{\boldsymbol{i,t}}$).[16] Formally, the first stage takes the following form:

$$GBAORD_{i,t} = \alpha_i + \delta_t + \beta_1 POST_{i,t} + \beta_2 ENERGY_i \times POST_{i,t} + \boldsymbol{\Omega}'_{\boldsymbol{i,t}}\Gamma + \epsilon_{i,t} \tag{2}$$

After instrumented, I estimate the causal effect of a change in the level of GBAORD on the three outcomes of interest.[17] The three second stages take the following form:

$$Y_{i,t} = \alpha_i + \delta_t + \beta_1 POST_{i,t} + \beta_2 \widehat{GBAORD}_{i,t} + \boldsymbol{\Omega}'_{\boldsymbol{i,t}}\Gamma + \epsilon_{i,t} \tag{3}$$

where $Y_{i,t}$ is, alternatively, *i)* the total number of citations received by green patent i at time t, *ii)* the number of citations from non-green patents received by green patent i at time t, or *iii)* the average technological distance of citations received by green patent i at time t; α_i and δ_t are, respectively patent and year fixed effects; $POST_{i,t}$ is the post-Chernobyl time indicator (1986–1988), taking value 1 for both energy and non-energy green patents; $\widehat{GBAORD}_{i,t}$ is the (instrumented) level of GBAORD affecting patent i at time t; the vector $\boldsymbol{\Omega}'_{\boldsymbol{i,t}}$ contains the set of time varying controls, as described in Sect. 3.2.2; $\epsilon_{i,t}$ is the error term.[18]

Dynamic effects of the Chernobyl nuclear accident on GBAORD As stressed in Sect. 3.3.1, the validity of the DiD strategy adopted in the first stage depends on the assumption that, in the absence of the Chernobyl shock, the pattern of GBAORD would not have been systematically different between energy and non-energy technological domains. Therefore, I test for pre-Chernobyl-trends in the level of GBAOD by looking at the full set

[16] The preferred model specifications include patent fixed effects and, therefore, drops the coefficient of the dummy variable *ENERGY*.

[17] All 2SLS models use a single instrument resulting in a just identified estimate.

[18] Since patent citations data have count nature, I also estimate Eq. 3 with Poisson and Poisson quasiMLE (Lin & Wooldridge, 2019), which need to be properly adapted to accommodate the IV strategy. The results of these robustness checks, available by the author upon request, confirm both qualitatively and quantitatively the main evidence reported in Sect. 4.3.

Table 1 Summary statistics

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

of lags and leads around the time of the nuclear accident ($k = -3, \dots, 2$; excluding -1) for energy and non-energy patents (L_{ik}). I estimate the following specification with OLS:

$$GBAORD_{it} = \sum_{k=-3}^{2} \beta_k 1_{\{l_{it}=k\}} + \beta^{All} \times Post_{it} + \alpha_i + \delta_t + \varepsilon_{it} \tag{4}$$

where $GBAORD_{it}$ is the log-transformed level of government R&D related to patent i in period t; the set of $\{\beta(k)\}_{k=-3}^{2}$ captures the dynamic effects associated with lags and leads; I include the period event indicator $Post_{it}$ that takes value 1 in the periods after the Chernobyl event and that is common to both treated (energy) and control (non-energy) green patents (the coefficient β^{All} captures the predicted effect of this indicators); lastly, I also include patent and time fixed effects (α_i and δ_t, respectively).[19]

4 Results

The main purpose of the empirical analysis is to test the expected positive effects of GBAORD on spillovers from green patents. As discussed in Sect. 3, to overcome endogeneity issues, I frame the empirical analysis in an instrumental variable setting. Therefore, I first estimate the first stage of the 2SLS models, predicting the level of GBAORD as a function of the Chernobyl shock in the energy domain and control variables (Eq. 2). After instrumented, I estimate the effect of a change in GBAORD on the three outcomes of interest (Eq. 3).

Before discussing the results of the main analysis, I provide empirical evidence of the opportunity to exploit the occurrence of the 1986 Chernobyl nuclear accident to capture exogenous variability in GBAORD.

4.1 Testing for dynamic effects of the Chernobyl nuclear accident

The DiD strategy adopted in the first stage is valid if, in the absence of the Chernobyl shock, the pattern of GBAORD would not have been systematically different between energy and non-energy domains.

[19] Periods refer to the years 1983–1988; period 0 corresponds to 1986. I drop the coefficient that refers to period −1 (1985) due to collinearity reasons.

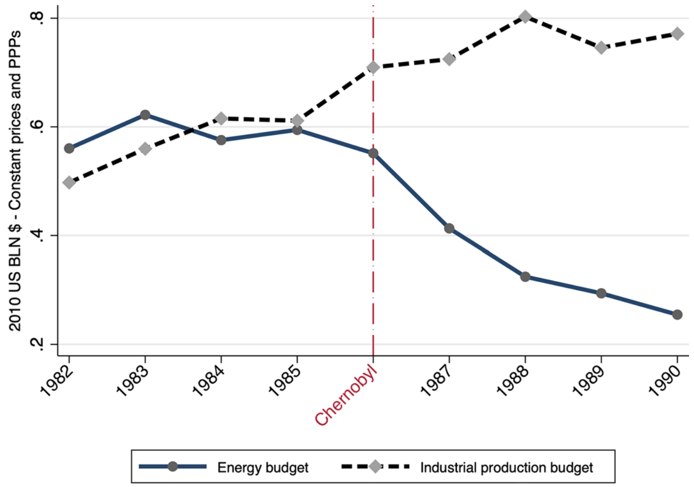

Fig. 1 GBAORD average level (energy vs. industrial production, 1982–1990). *Notes*: The figure plots the average level (in 2010 BLN US$, constant-prices and PPPs) of energy-related GBAORD andindustrial production-related GBAORD (dashed line) in selected EU countries between 1982 and 1990. *Source*: Author'selaboration on OECD (2017) data

To test for the absence of pre-trends in GBAORD across technological domains, I estimate the model specification formalized by Eq. 4.

Figure 2 plots point estimates of the dynamic effects associated with lags and leads around the Chernobyl accident (i.e., the set of β coefficients related to GBAORD in Eq. 4). The sharp drop in energy-related GBAORD in 1986 confirms the expected negative effect of the Chernobyl nuclear accident, which was immediate. Moreover, this negative effect lasted in the following years, oscillating between approximately -37% (year 1986) and -59% (year 1988).

Importantly, this empirical setting allows us to formally test the hypothesis that point estimates are the same before and after 1986. The null hypothesis is:

$$H_0^{before} : \beta_{-3} = \beta_{-2}$$
$$H_0^{after} : \beta_2 = \beta_1 = \beta_0$$

The results of this test, reported in Table 2, indicate that we cannot reject the hypothesis that point estimates are all the same before 1986, but we can since 1986. In other words, they show that there were no pre-trends but an effect on GBAORD in the year of the Chernobyl nuclear accident and in the two years after.

4.2 First stage results

We now turn to the results obtained from the first stage of the 2SLS models formalized by Eq. 2. First stage results are reported in Table 3. Column I reports the results when the model specification includes, together with the interaction of interest $ENERGY_i \times POST_{i,t}$, the post-Chernobyl indicator $POST_{it}$, patent fixed effects and

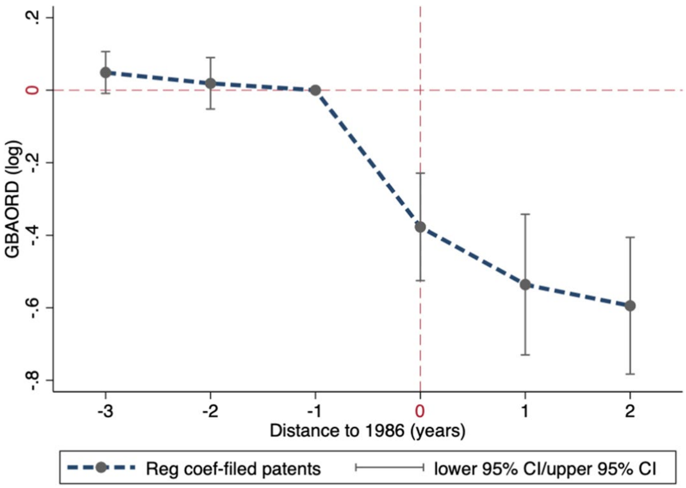

Fig. 2 The effect of the Chernobyl nuclear accident on GBAORD. *Notes*: The figure plots point estimates of the dynamic effects associated with lags and leads around the Chernobylaccident (i.e., the set of β coefficients in Eq. 4)

Table 2 Testing for dynamic effects, *p* values from F-test

	For H_0^{before}	For H_0^{after}
p values of F-tests for equality of the β_k coefficients	0.3019	0.0001

The table reports the *p* values of F-tests for equality of the β_k coefficients from Eq. 3, before and after the Chernobyl nuclear accident (1986), as specified by the hypotheses H_0^{before} and H_0^{after}

calendar year fixed effects. The magnitude of the coefficient for the interaction term $ENERGY_i \times POST_{i,t}$ (the DiD variable capturing the effect of the Chernobyl accident on GBAORD in energy) is − 0.399, meaning that GBAORD, on average, dropped by 39.9% as a consequence of the Chernobyl accident in energy, compared to non-energy fields.

Columns II to IV report the results when we augment the model with, separately, *BERD* (column II), *Emission intensity* (column III) and *Oil price* (column IV). Column V reports the results when we saturate the model by including all control variables together (Eq. 2). The coefficient of the interaction of interest ($ENERGY_i \times POST_{it}$) is stable in terms of both significance and magnitude across all specifications, ranging between − 0.399 and − 0.404.[20] Lastly, the F-statistics of excluded instruments are always above the threshold of 10, confirming that the instrument is not weak (Staiger & Stock, 1997).

Overall, the results from the first stage corroborate the hypothesis that the nuclear accident occurred in Chernobyl in 1986 had a significant negative effect on the level of GBAORD targeting energy green patents.

[20] In more demanding specifications, *country* × *year* and *sector* × *year* fixed effects have been included. The results of these robustness checks, available upon request, confirm the main evidence.

Table 3 First stage results

	Dependent variable: GBAORD (log)				
	(I)	(II)	(III)	(IV)	(V)
Energy × post	– 0.399***	– 0.399***	– 0.404***	– 0.399***	– 0.404***
	(0.0038)	(0.0039)	(0.0039)	(0.0038)	(0.0040)
Post Chernobyl	0.126***	– 0.024**	0.816***	0.077***	0.422***
	(0.0045)	(0.011)	(0.010)	(0.0064)	(0.0087)
BERD (log)		0.402***			0.222***
		(0.030)			(0.030)
Emission intensity			0.722***		0.711***
			(0.0080)		(0.0077)
Oil price (log)				– 0.045***	– 0.268***
				(0.0038)	(0.0059)
Patent FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	99,002	99,002	99,002	99,002	99,002
Adj. R^2	0.160	0.173	0.365	0.160	0.369
F-stat	16.55	16.55	16.28	16.55	16.27

Robust standard errors are in parentheses

$^*p < .1$; $^{**}p < .05$; $^{***}p < .01$

4.3 Second stage results

I then estimate the effect of changes in GBAORD on the three outcomes of interest. Table 4 reports the results obtained from estimating the three second stages. The first stage—the same for all models estimated in the second stages—is reported in Table 3, column V.

The first focus is on the total (log transformed) number of citations received by green patents (column I). This step serves the goal of estimating the impact of GBAORD on broad technological spillovers generated by GTs. Results show that the coefficient of GBAORD is positive and significant. Precisely, a 10% increase in GBAORD leads to around 0.7% increase in the number of citations received by green patents. At least two reasons could explain the small magnitude of the estimated GBAORD coefficient. First, it is worth to notice that GBAORD captures the overall level of budget in government R&D. During the period 1981–1988, only a small amount of GBAORD targeted environmentally-related projects.[21] Therefore, it is reasonable to assume that only a small fraction of a GBAORD increase could be responsible for the small estimated increase in overall green patent citations. In other words, if the hypothetical 1% increase in GBAORD were entirely devoted to green R&D projects, it is very likely that the positive effect on citations would be considerably greater. Second, previous evidence in the field of alternative energy technologies (i.e. biofuels, energy efficiency, solar energy and wind energy) reported by Popp (2016) shows that expanding public R&D budget leads to scientific advances with future technological impact, but with large temporal lags (also more than ten years). Indeed, Popp

[21] For example, in 1990 the US renewable energy public RD &D budget represented 4.35% of the total energy public RD &D (OECD Green Growth Indicators).

(2016) concludes that "*the impact of any such expansion may not be realized for some time*" (p. 1). Given the relatively short period analyzed here, it is therefore reasonable to estimate a significant but small effect.

As for the control variables, the coefficient of *BERD* is not significant. This result is not surprising because BERD captures the overall level of private R&D that, at that time, was only peripherally related to green innovation. As for *Emission intensity*, its coefficient is negative and significant, meaning that low levels of environmental policy pressure (i.e. high levels of emission intensity) are associated to low levels of GT spillovers, as expected. Lastly, the coefficient of *oil price* is positive and significant, meaning that an increase in the cost of fossil fuels leads to more innovation around GTs, as expected.

Overall, these results provide support to the first hypothesis stated in Sect. 2, according to which increasing government R&D budgets leads to higher technological spillovers generated by GTs.

We then turn to the discussion of the results obtained from the second and third step of the analysis, respectively. In Table 4, column II we report the results when the dependent variable is the (log transformed) number of forward citations received by green patents from non-green patents. Also in this case, the coefficient of *GBAORD* is positive and significant, with a magnitude similar to previous estimates (i.e. 0.07). This result provides support to the second hypothesis of the paper: GBAORD fosters green technological spillovers that benefit also traditional, non-green domains. This suggests that government R&D could be a powerful policy lever to accelerate the process of technological hybridization. However, even in this case we note the small magnitude of the estimated coefficient, confirming that this process could take a long time to materialize substantially.

About the control variables, we estimate coefficients with significance and magnitude similar to the former specification. The only remarkable difference is for the variable *oil price*, whose coefficient is sensibly lower than the one reported in column I.

Table 4 Second stage results

	Dependent variables		
	Tot citations (log)	Dirty citations (log)	Tech distance
	(I)	(II)	(III)
GBAORD (log)	0.066***	0.070***	0.008***
	(0.016)	(0.010)	(0.000)
Post Chernobyl	0.165***	0.056***	0.002***
	(0.021)	(0.015)	(0.000)
BERD (log)	− 0.001	− 0.019	− 0.002***
	(0.021)	(0.015)	(0.001)
Emission intensity	− 0.082***	− 0.060***	− 0.008***
	(0.015)	(0.010)	(0.000)
Oil price (log)	0.139***	0.036**	− 0.001
	(0.020)	(0.015)	(0.000)
Patent FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	99,002	99,002	99,002

Robust standard errors are in parentheses. First stage reported in Table 3, column (V)

*$p < .1$; **$p < .05$; ***$p < .01$

In column III we report the estimates of the effect of *GBAORD* on the technological distance of patents citing GTs (testing the third hypothesis of the paper). The estimated coefficient of *GBAORD* is positive and significant, meaning that increasing government R&D budgets significantly enlarges the breadth of technological spillovers originated from GTs. Precisely, a 1% increase in GBAORD leads to.008 increase in the technological distance index described in Sect. 3.2.1. Since the average *Tech distance* of the patents in the sample is 0.008 (SD 0.016), the estimated effect of *GBAORD* has therefore economic relevance.

As for the control variables, the coefficients of both *BERD* and *Emission intensity* are significant and negative. About the negative coefficient of *BERD*, this is likely due to path dependence in innovation processes: R&D expenditures tend to be oriented towards specialization, which reduces the average technological distance between new and previous innovation processes. The interpretation of the negative effect of *Emission intensity* adds an interesting insight to what discussed above: low levels of environmental policy pressure are indeed associated not just to a decrease in overall green spillovers but also to a lower technological distance of the inventions that make use of extant green knowledge, possibly limiting technological diversification. Lastly, *oil price* does not show a significant coefficient.

4.4 Robustness checks

4.4.1 Further controls and different model specifications

The first robustness check concerns possible patent scale effects. To provide a first check of the validity of the main analysis, I add the annual number of green patents at the SEO-country level (*Tot Pat*) to the set of control variables. The second stage results of these tests (Table 5, columns I) confirm the main findings. Indeed, the estimated coefficients of *GBAORD* are positive and statistically significant, showing magnitudes similar to the main estimates reported in Table 4.

I then check the robustness of the main analysis also to different estimators and model specifications. First, I remove patent fixed effects and I include the dummy *ENERGY*, estimating the models with simple OLS (Table 5, columns II). Second, I augment these models with the inclusion of country and technology (IPC 4-digit) fixed effects (Table 5, columns III). Third, I further augment these models controlling also for time invariant patent characteristics (i.e., number of claims, number of backward citations, number of inventors) (Table 5, columns IV). Lastly, I include patent age dummies instead of year dummies, both with and without patent fixed effects (Table 5, columns V and VI). Overall, the results are robust to all checks described: the estimated effect of GBAORD on the three outcomes of interest is indeed positive and significant across all specifications, with magnitudes similar to the magnitudes reported in the main analysis.

Moreover, first stage results are fully consistent with first stage results reported in Table 3. Precisely, the coefficient of $ENERGY_i \times POST_{it}$ ranges between − 0.37 and − 0.40 (the estimated coefficient of $ENERGY_i \times POST_{it}$ reported in Table 3 is − 0.40).

4.4.2 Germany invented patents

As stressed in footnote 12, the World Bank database does not provide data on emission intensity for Germany before 1991. I therefore exclude patents invented in Germany from the main analysis. However, a high number of GT patents were invented in West Germany

Table 5 Further controls and different model specifications

	(I)	(II)	(III)	(IV)	(V)	(VI)
Second stage results						
A. Dependent variable: Tot citations (log)						
GBAORD	0.071***	0.091***	0.089***	0.084***	0.062***	0.047***
	(0.017)	(0.022)	(0.022)	(0.021)	(0.020)	(0.016)
B. Dependent variable: Dirty citations (log)						
GBAORD	0.052***	0.083***	0.081***	0.078***	0.066***	0.059***
	(0.010)	(0.014)	(0.014)	(0.014)	(0.013)	(0.010)
C. Dependent variable: Tech distance						
GBAORD	0.004***	0.009***	0.009***	0.009***	0.008***	0.007***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Control variables						
Main controls	✓	✓	✓	✓	✓	✓
N. of patents	✓	–	–	–	–	–
Energy (dummy)	–	✓	✓	✓	✓	–
Further controls	–	–	–	✓	–	–
Patent FE	✓	–	–	–	–	✓
Year FE	✓	✓	✓	✓	–	–
Patent age FE	–	–	–	–	✓	✓
Country FE	–	–	✓	✓	–	–
Technology FE	–	–	✓	✓	–	–
Observations	99,002	99,002	99,002	99,002	99,002	99,002
First stage results						
Dependent variable: GBAORD						
Energy × post	– 0.40***	– 0.37***	– 0.37***	– 0.37***	– 0.38***	– 0.40***
	(0.004)	(0.035)	(0.034)	(0.034)	(0.035)	(0.004)
F-Stat	18.04	20.71	20.28	17.94	10.45	8.07

Main controls is the vector of time-varying control variables used in Table 4. *N. of patents* is the number of patents calculated at the sector-technology level. *Energy* is a dummy variable for energy-related patents. *Further controls* is a vector of fixed patent characteristics such as number of claims, number of backward citations and number of inventors. *Patent Age* is the difference between year of observation and patent priority year. *Country* is assigned to patents according to the inventor's country of residence. *Technology* are IPC 4-digit dummies. First stages are common to A, B and C panels. Robust standard errors are in parentheses

*$p < .1$; **$p < .05$; ***$p < .01$

during the 1980s. Therefore, I provide a set of robustness checks including these patents in the sample. To do so, in a first set of estimates I remove *Emission Intensity* from the control variables. Moreover, I also provide further robust evidence substituting the (log transformed) level of GBAORD targeting the environment (*GBAORD env*) for *Emission Intensity*. Results are reported in Table 6. Panel B reports the first stage results. Column (a) excludes *Emission Intensity* from the set of control variables, while column (b) substitutes *Emission Intensity* with *GBAORD env*. Panel A reports the second stage results, taking as dependent variables, respectively, the total number of citations, the number of citations from non-green patents and the average technological distance to green patents of the citations received. Columns a.I, a.II

Table 6 Inclusion of DE patents

Panel A: Second stage results

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

Panel B: First stage results

	Dependent variable: GBAORD (log)	
	Exclusion *Emission Intensity*	Inclusion *GBAORD Env*
	(a)	(b)
Energy × Post	− 0.487***	− 0.491***
	(0.0035)	(0.0038)
F-stat	25.23	25.29

Panel A reports the second stage results. Columns a.I, a.II and a.III are based on the first stage reported in Panel B, column a. Columns b.I, b.II and b.III are based on the first stage reported in Panel B, column b. Columns (a) exclude *Emission Intensity* from the set of control variables; columns (b) substitute *Emission Intensity* with GBAORD related to the environment (*GBAORD env*). The sample used is the main sample augmented with the inclusion of patents filed by German inventors between 1980 and 1984. Robust standard errors are in parentheses

*$p < .1$; **$p < .05$; ***$p < .01$

and a.III are based on the first stage reported in Panel B, column (a). Columns b.I, b.II and b.III are based on the first stage reported in Panel B, column (b).

Overall, the results of these robustness checks confirm the main findings reported in Table 3 and in Table 4. Looking at the first stage (Panel B), the estimated negative impact of the Chernobyl accident on the level of GBAORD is larger than what previously found, reaching around -49% in both samples (columns a and b). As for the effect of GBAORD on the three outcomes of interest (Panel A), I estimate significant positive coefficients, whose magnitudes are slightly lower than what found for the main sample (i.e. comparing Table 6, Panel A with Table 4). Precisely, when the dependent variable is the total number of citations, the estimated coefficient for GBAORD decreases from.066 to.056 (column a.I). Similarly, when the dependent variable is the number of citations from non-green patents, the coefficient of GBAORD decreases from.070 to.057 (column a.II). Similarly, the impact of GBAORD on the average technological distance of patents citing green patents decreases from.008 to.006.

These coefficients are statistically stable when *GBAORD Env* enters the set of control variables (columns b.I, b.II and b.III), reassuring about the robustness of the results obtained with the main analysis.

4.4.3 US and UK invented patents

Due to deregulation and privatization of the energy sector, a sharp decline in public R&D for energy technologies started since the early 1980s in the US (Margolis & Kammen, 1999). During the 1980s, similar policy interventions were implemented also in the UK. Therefore, I exclude both US- and UK-invented patents from the analysis to provide further robustness checks. Results from this reduced sample of patents are reported in Table 7 and confirm the main findings discussed in Sects. 4.2 and 4.3. Looking at the first stage (Panel B), the estimated negative impact of the Chernobyl accident on the level of GBAORD is the largest, reaching − 61.4%. As for the second stage results (Panel A), I find significant positive coefficients whose magnitudes are slightly lower than what found for the main sample. Precisely, when the dependent variable is the total number of citations, the estimated coefficient for GBAORD decreases from.066 to.058 (column I). Similarly, when the dependent variable

Table 7 Exclusion of US and UK patents

Panel A: Second stage results

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

Panel B: First stage results

	Dependent variable: GBAORD (log)
	(I)
Energy × Post	− 0.614*** (0.0073)
F-stat	16.17

Panel A reports the second stage results. Columns I, II and III are based on the first stage reported in Panel B. The sample used is the main sample reduced due to the exclusion of patents filed by US or UK resident inventors. Robust standard errors are in parentheses

**p* < .1; ***p* < .05, ****p* < .01

is the number of citations from non-green patents, the coefficient of GBAORD decreases from .070 to .049 (column II). Similarly, the impact of GBAORD on the average technological distance of patents citing green patents decreases from .008 to .005 (column III).

5 Conclusions

Simultaneously fostering the emergence of breakthrough GTs and substituting traditional emitting technologies with existent GTs are crucial policy targets for guaranteeing long-run growth. Given the level of advance of traditional technologies and the cumulative nature of innovation processes, public support is indispensable for filling the secular technological gap between environmentally friendly and traditional technologies. Long-term sustainability goals might however hamper short-run growth. Shifting public support from traditional to green technologies might indeed cause short-run losses if, for example, the latter systematically generate lower technological spillovers than the former.

The present paper contributes the literature on policy-driven green technical change by providing evidence of the causal effect of changes in government R&D on technological knowledge spillovers from GTs. The empirical analysis leverages the exogenous occurrence of the Chernobyl nuclear accident to provide causal estimates of the relationship between public R&D and green knowledge spillovers. Investigating the rate and the direction of patent citations received by EP green patents filed between 1980 and 1984, results show a significant positive effect of increasing government R&D budget on overall green technological spillovers. Since the importance of spillovers for growth is well documented, public R&D targeting green innovation is very likely to be beneficial for economic growth, also in the short run. However, the estimates show low coefficients, confirming previous evidence that positive effects of public R&D on green knowledge take time to materialize (Popp, 2016). Moreover, results show that public R&D is a tool to enhance the entry of green knowledge into traditional innovation processes. This is likely to facilitate and accelerate technological hybridization, a crucial step to timely and efficiently achieve the transition towards sustainable production methods. The role of public R&D could be, therefore, twofold: on the one hand, it could target green projects with high potential in terms of applicability to traditional processes; on the other, it could be directed towards traditional processes with the highest probability of being efficiently hybridized. Lastly, the paper also documents the positive role of public R&D in enlarging the spectrum of invention processes benefiting from green knowledge spillovers. This means that GT spillovers spread across technologies favored by higher public investments in R&D, feeding distant and heterogeneous (green and traditionally non-green) domains. Overall, the second and the third main result combined provide evidence that public R&D fosters not just the level of spillovers from GTs but also their pervasiveness across heterogeneous domains, favoring technological diversification. This will benefit systemic technological dynamism, reducing the risks associated with technological lock-ins and opening new opportunities of technological hybridization.

From a policy perspective, given the documented positive but low effect on generated knowledge spillovers, a considerable re-balance of government R&D budget towards green projects seems to be required. Importantly, this shift will very unlikely hamper short-run growth and will favor technological diversification and hybridization. In other words, shifting government R&D towards green innovation would be a lever for achieving the win-win desired outcome of guaranteeing long-run sustainability while keeping economic growth on a sustained pattern. Therefore, governments should not hesitate in taking action, directing government R&D towards green projects with wider applicability potential to increase their effectiveness in terms of green knowledge pervasiveness.

The paper has inevitable limitations that might open future research lines. First, the analysis focuses on the early-stage phase of development of GTs in a particular period (i.e., the 1980s), raising questions about whether we can generalize the results obtained. Hence, future research should focus on more recent periods (and, possibly, on a broader set of new GTs) to consolidate and advance our understanding of the link between public R&D and GT spillovers. Second, the paper focuses on GTs in general, without appreciating their heterogeneity. Therefore, future studies might conduct finer systematic investigation to appreciate heterogeneous effects of public R&D on spillovers according to different kinds of GTs. Third, the analysis is silent about the direct comparison between spillovers from green *vis-à-vis* dirty technologies. One promising future research line would be therefore to explicitly focus on this distinction and, moreover, to investigate whether the composition of citations made by dirty technologies changes because of changes in the level and in the direction of public R&D. Lastly, the analysis looks at public R&D broadly and without considering its coexistence with other policy tools, both demand and supply oriented. Therefore, future research might focus on specific (possibly only green) public R&D projects and, systematically, on their joint interplay with other policy tools.[22]

Appendix

Overview of the energy generation context

The energy sector experienced a structural reconfiguration during the 1970s and the 1980s, mainly due to the energy crises occurred in 1973 and 1979. With the aim of guaranteeing economic sustainability and self-sufficiency of the energy production system, an important wave of investments in alternative energy generation technologies took place worldwide, starting from the 1970s. This process was driven by vast investments in nuclear technologies.

As an example, Fig. 3 plots the number of new nuclear reactors connected worldwide to the grid by commercial operation year, during 1954–2010. The upsurge was continuous since the beginning of the series, increasing during the 1970s and reaching a notable peak in 1985, just before the Chernobyl nuclear accident. Afterwards, a sharp decline occurred, with the number of new reactors connected to the grid falling to less than ten per year since 1990.

To provide another example, the share of electricity produced from nuclear sources in Europe increased from about 2 percent in the early 1970s to about 35 percent in 1990, stabilizing at that level afterward (see Fig. 4).[23] Conversely, the share of electricity production

[22] About recent literature on the policy mix, see Guerzoni and Raiteri (2015) and Costantini et al. (2017) among others.

[23] Fossil fuel combustion is responsible for approximately 65 percent of global greenhouse gas emissions (US Environmental Protection Agency). Of these emissions, coal contributes for 45%, oil for 35% and natural gas for 20% (Carbon Dioxide Information Analysis Center). The major sectors demanding fossil fuels are the electricity and the transportation sectors. Having a descriptive look at the electricity sector is thus informative in our context.

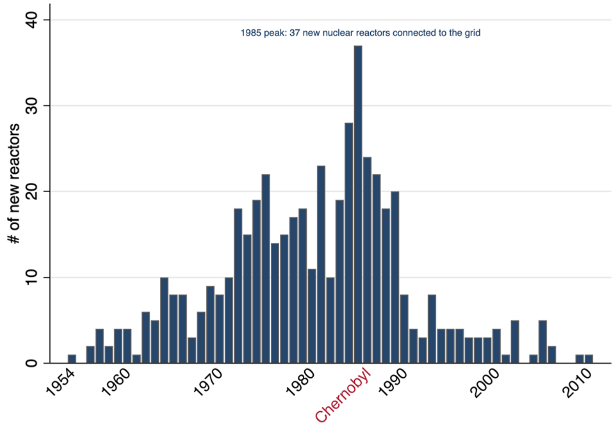

Fig. 3 Number of new nuclear reactors connected to the grid (1954–2015). *Notes*: The figure plots the number of new nuclear reactors connected to the grid worldwide between 1954 and 2015 *Source*: Author's elaboration on IAEA (2016) data

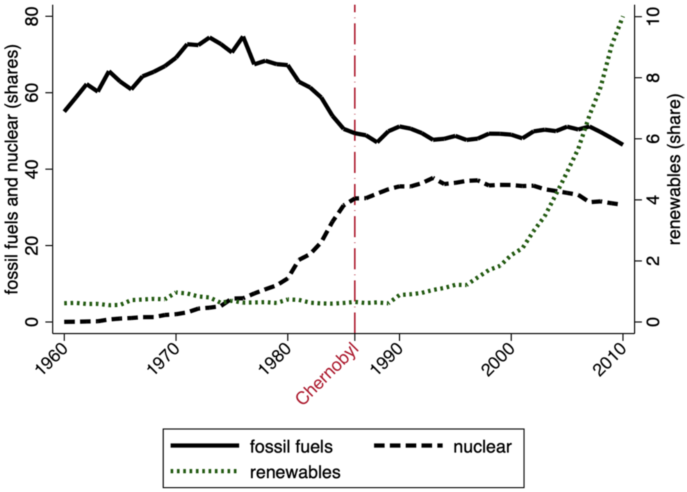

Fig. 4 Electricity production by source, shares (EU, 1960–2010). *Notes*: The figure plots the share contribution of fossil fuels, nuclear and renewables to electricity production in EUcountries between 1960 and 2010. Hydroelectric not considered. *Source*: Author's elaboration on World Bank (2017) data

from fossil fuels (oil, gas and coal) fell from about 70% to about 50% in the same period for European countries. The US experienced very similar patterns.

As for renewable sources (e.g. solar and wind), a public push for their development started in the late 1970s. The first on-shore wind farm (0.6 MW) was installed in southern New Hampshire (US) in December 1980 and, similarly, the first photovoltaic park was launched in the US at the end of 1982. However, looking again at the electricity generation sector (Fig. 4), the share of its production from renewable sources was almost irrelevant up to the end of the last millennium (abundantly below 2% worldwide), revealing a long pattern of stagnation. Behind this two decades congestion experienced by renewable sources there is their enormous cost to be afforded in making them competitive, combined with the scarce environmental policy pressure that characterized the 1970s and 1980s worldwide. About this last point, Fig. 5 plots the number of new policy tools implemented by IEA countries since the early 1970s. A first wave of policy intervention was concentrated

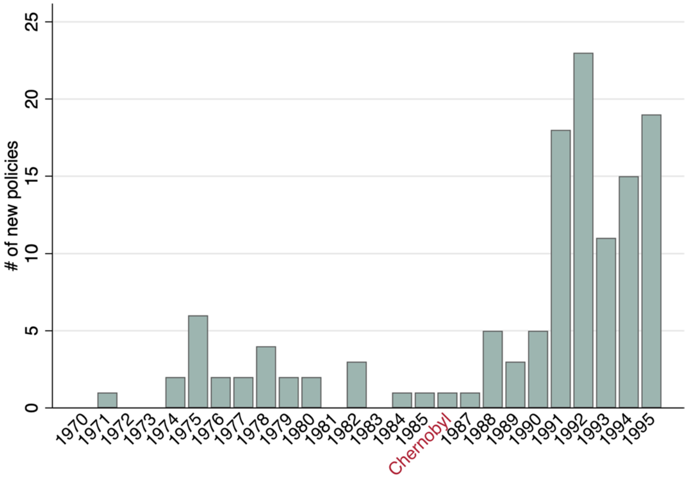

Fig. 5 Number of new environmental policies (IEA countries, 1970–1995). *Notes*: The graph reports the number of new environmental policy tools implemented by IEA Member Countries between1970 and 1995. *Source*: Author's elaboration on IEA (2017) data

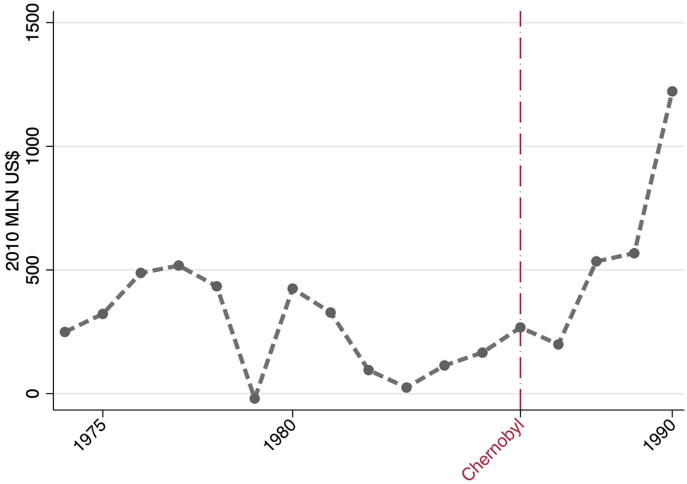

Fig. 6 US-Gov energy-R&D expenditure: difference between fossil-fuels and renewables (1974–1990). *Notes*: The figure plots the difference (in 2010 MLN USD) between US government R&D in fossil fuels and in renewablesources between 1974 and 1990. *Source*: Author's elaboration on OECD/IEA (2017) data

between 1974 and 1980. Then, during the 1980s the effort sensibly reduced. A decisive policy boost finally started in the early 1990s.

To sum up, the policy architecture to limit the dependence from fossil fuel sources was based on nuclear power until the mid-1980s and, therefore, the whole policy architecture for the enhancement of energy generation technologies alternative to fossil fuels was exogenously influenced by the Chernobyl accident, negatively.

Figure 1 in the main text provides descriptive evidence in this sense. Similarly, Fig. 6 draws the difference in the level of the US government R&D expenditures between fossil-fuel and renewable sources. After a minimum experienced in 1979 as a response to the second oil crisis, in 1986 the divergence between the two sources returned to the early-1970s levels. Afterwards, a tremendous increase is evident, confirming a restored relative interest by the US government in supporting R&D for fossil-fuel sources. According to Bointner (2014), US public renewable energy R&D expenditures indeed peaked in Carter's last year of presidency in 1980, leading to a first knowledge maximum in 1985 and decreasing afterwards.

The stylized evidence discussed in this section suggests that, in relative terms, the fall in government R&D due to the Chernobyl accident was mainly driven by reducing public resources to alternative to fossil fuel technologies.[24]

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[24] It must be stressed that a sharp decline in government R&D for energy technologies in the US started since the early 1980s (Margolis & Kammen, 1999) Therefore, in a robustness check discussed in Sect. 4.4 I exclude US invented patents from the sample. Results confirm the main analysis.

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