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Public R&D and green knowledge diffusion:
Evidence from patent citation data

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Abstract

The present paper investigates the relationship between public R&D and the diffusion of green knowledge. To do so, we exploit information contained in green patents filed at the European Patent Office from 1980 to 1984. The diffusion of green knowledge is measured by meaning of patent citations. The level of public R&D is instrumented through the policy reaction to the 1986 Chernobyl nuclear accident – that affected the level of public R&D in the energy generation domain – in a difference in differences setting. Results show that a 10% increase in public R&D increases by around 0.7% the number of citations to green patents. Moreover, increasing public R&D fosters the diffusion of green knowledge across traditional (non-green) domains and increases the average technological distance of inventions citing green patents. This evidence suggests that public R&D is a driver of green knowledge diffusion, accelerates the hybridization of traditional innovation processes and fosters technological diversification.

Keywords: Public R&D, Green innovation, Knowledge diffusion, Patent citations, Environmental policy, Green R&D

R & D publique et diffusion des connaissances vertes : Une analyse empirique sur les citations de brevets

Résumé

Le présent article examine la relation entre la R & D publique et la diffusion des connaissances technologiques vertes. Il exploite les informations contenues dans les brevets verts déposés à l'Office européen des brevets de 1980 à 1984. La diffusion des connaissances technologiques vertes se mesure au sens des citations de brevets. Le niveau de la R & D publique est instrumenté par la réaction politique à l'accident nucléaire de Chernobyl en 1986 qui a affecté le niveau de R & D publique dans le domaine de la production d'énergie. Les résultats montrent qu'une augmentation de 10% de la R & D publique augmente d'environ 0,7% le nombre de citations reçues par les brevets verts. En outre, l'intensification de la R & D publique favorise la diffusion des connaissances technologiques vertes dans les domaines traditionnels (non verts) et accroît la distance technologique moyenne des inventions citant des brevets verts. Cela suggère que la R & D publique est un moteur de diffusion des connaissances vertes, accélère l'hybridation des processus d'innovation traditionnels et favorise la diversification technologique.

Mots-clés: R & D publique, Innovation verte, Diffusion des connaissances, Citations de brevets, Politique environnementale, R & D environnementale

JEL: O30, O32, O33, O38, Q55

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1 Introduction[1]

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

Innovation plays a crucial role. To guarantee long-run sustainable growth, public interventions – both market and R&D oriented – are required at least until green technologies (hereafter GTs) will overcome the sunk-cost advantage of incumbent technologies (Acemoglu et al., 2012). On the one hand, GTs suffer for the common knowledge market failures. The public goods nature of knowledge leads to appropriability issues that, in turns, reduce incentives to innovate. On the other hand, if the market does not correctly price environmental externalities, the demand for GTs is limited and firms have scarce incentives to invest in green R&D. This so-called 'double-externality' problem must be addressed by meaning of combined *technology-push* and *demand-pull* policies (Rennings, 2000).

Empirical literature largely confirms this solid theoretical framework, showing that both correctly pricing pollution and subsidizing green R&D induce innovation in GTs. However, governments may also play a direct role in spurring GTs through specific public R&D.[2] Surprisingly, the role of public R&D for green innovation has been poorly investigated. Importantly, while the generation and diffusion of GTs has clear, positive consequences on the environment, less has been said about its impact on new knowledge creation and diffusion. To sum up, the relationship between public R&D, GTs and the diffusion of green knowledge deserves more systematic empirical ground.

The present paper aims at filling this gap by studying the causal effect of changes in public R&D on the diffusion of green knowledge. It formulates three main hypotheses about the relationship under scrutiny. Drawing from the policy inducement literature, the first hypothesis claims that increasing the government budget for R&D leads to higher rates of usage of extant green technological knowledge. Briefly, this is essentially due to the attenuating effect of public policies on externalities attached to GT investments. Then, the paper more deeply elaborates on the technological content of inventions making use of established green knowledge. Precisely, it investigates whether public R&D fosters the diffusion of green knowledge into distant technological domains and, importantly, into innovation processes that pertain to non-green (dirty) technological trajectories. Indeed, if public R&D fosters a broader diffusion of green knowledge this is likely to raise the probability of obtaining disruptive technical advances.[3] Furthermore, if R&D also fosters the entry of green knowledge in traditional, non-green innovation activities, it is reasonable to expect a faster substitution between dirty and clean technologies. The two main hypotheses here are that, due to the combination of the intrinsic characteristics of green innovations and the basicness and broader applicability of publicly-generated knowledge, increasing public R&D boosts the use of

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[2] Throughout the paper the expressions "public R&D", "publicly-funded R&D", "publicly-conducted R&D", "government R&D", "government-funded R&D" and "government budget for R&D" are used interchangeably.

[3] By investigating the relationship between innovation complementarity and environmental productivity at the EU level, Gilli et al. (2014) conclude that incremental strategies dominated radical strategies so far, leading to insufficient results when looking at long-run economic and environmental goals. Fostering radical attempts seems thus a real priority.

green knowledge by both technologically distant and non-green innovation processes. Both mechanisms have direct implications for technological hybridization and economic growth.

To test the three working hypotheses, we analyze the early stage phase of development of GTs. Precisely, we exploit patent information data, considering all green patents filed at the European Patent Office from 1980 to 1984 – together with their citation patterns.

To overcome endogeneity issues characterizing the relationship between technical advance and public intervention, we rely on the unexpected occurrence of the Chernobyl nuclear accident (April 1986) as an exogenous shock for the design of policies targeting the energy generation domain. According to the arguments proposed in Section 3, the policy reaction to the Chernobyl nuclear accident allows to instrument the level of public R&D. Once instrumented, we estimate the effect of changes in public R&D on the rate and direction of green knowledge diffusion.

Results show that increasing the level of public R&D fosters overall green knowledge diffusion and, importantly, the use and reuse of established green technological knowledge by both distant technologies and technologies not directly classified as environmentally friendly. Therefore, public R&D is an important lever for both consolidating the established green technological trajectory and accelerating the hybridization of traditional processes.

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

2 Theoretical background and hypotheses

The uniqueness of green innovation processes traditionally resides in two well documented theoretical arguments, summarized by the so-called 'double-externality' concept (Rennings, 2000): first, by attenuating environmental damages, the adoption and diffusion of GTs generate positive externalities that firms cannot fully internalize if the market does not optimally price pollution; second, as for any other innovation process, firms are systematically not able to entirely capture the social value of performed green R&D, due to the intrinsic characteristics of (partial) non-rivalry and non-excludability of technological knowledge. This double issue leads to constant under-investments in green R&D. Compensatory public intervention is therefore indispensable to restore efficiency (Jaffe et al., 2002). Starting from this consciousness, since the mid-1990s the literature investigating the mechanisms through which green innovation processes respond to policy interventions has experienced a tremendous upsurge.

2.1 Public R&D and green knowledge diffusion

During the last decades a variety of policy schemes and tools has been implemented to foster both the demand- and the supply-side of green innovation.

Demand oriented policies act in modifying consumer preferences, changing long-term consumption patterns. Examples of demand interventions include greenhouse gas emission targets, environmental standards, or carbon taxes. These tools represent an indirect stimulus to develop GTs. Supply-side policies, conversely, represent a direct support for technological change. They include subsidies, loans, tax credits, grants, pricing schemes, R&D funding for risky innovative processes, and so on.

While indirect stimuli would be suitable to foster the introduction and the spreading of existent, mature GTs, direct stimuli would instead be more likely able to create the ground for the generation of technological novelties (i.e. less mature technologies) with breakthrough potential (Nemet, 2009; Hoppmann et al., 2013; Costantini et al., 2015).

Browsing the extensive literature investigating the role of different types of instruments in shaping eco-innovation activities, we can conclude that the evidence of a strong policy effect on the generation and diffusion of GTs is crystalline.[4] However, only few studies specifically focus their attention on the role of government-funded R&D in fostering GTs, mainly related to the energy sector.

Klaassen et al. (2005) examine the impact of (subsidy-induced) capacity expansion and public R&D expenditures on cost reducing innovation for wind turbine farms in Denmark, Germany and the UK during the 1990s by both reviewing the extant literature and proposing a finer empirical analysis. The proposed survey of the literature suggests that R&D policy in Denmark was most successful in supporting innovation, and capacity promoting subsidies were most effective in Denmark and Germany in stimulating innovation. From their empirical analysis they conclude that results support the validity of the two-factor learning curve formulation, in which the cost reductions are explained by cumulative capacity and the R&D-based knowledge stock.

Sagar and van der Zwaan (2006) discuss aspects of public R&D and 'learning by doing' again in the energy realm. They conclude that "[s]*till, however uncertain the precise payoff of spending in research and development may be, there is little doubt that public ER&D budgets ought to be maintained, and probably increased, if we are to seriously address global problems such as climate change. The prime reason is that R&D efforts have been the basis for historical changes in energy production and conversion, and will underlie the technological changes that need to occur for transitioning to a sustainable energy system. Given the public-goods aspects of such a transition, the government's role will remain crucial*" (pag. 2607).

Bointner (2014) estimates the level of the cumulative energy knowledge stock induced by public R&D expenditures in 14 IEA-countries from 1974 to 2013, with specific emphasis devoted to renewable knowledge. The author concludes that "[o]*n total, public energy R&D expenditures were increasing over the last five to ten years and, thus the cumulative knowledge stock is currently also increasing*" [pag. 745]. As for the renewable energy knowledge stock, the analysis shows that heterogeneous patterns emerge according to the technology type and between countries.

An emerging strand of literature recently started exploring the linkages between university, research centers and industry for the generation of GTs. 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 and Meliciani (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

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[4] 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, 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).

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.

Due to the 'double-externality' issue characterizing GTs and according to the evidence reviewed above, we formulate the following hypothesis:

H1: *Increasing public R&D fosters the diffusion of green technological knowledge.*

2.2 Public R&D and the direction of green knowledge diffusion

As highlighted by Ghisetti et al. (2015), environmental innovation processes are characterized by intrinsic systemic nature and general purpose content. GTs require, on average, the combination of more heterogeneous and distant knowledge than other innovations to be performed (Renning and Rammer, 2009; Nemet, 2012; Horbach et al., 2013; Benson and Magee, 2014). This reflects also in the way how inventors recombine previous knowledge. Exploiting information on patenting activity at EPO during the period 1995-2009, Orsatti et al. (2017) argue that inventor teams with higher ability in creatively recombining previous knowledge are the ones that more likely introduce GTs.

The complexity associated with environmental innovation processes is likely to generate technological knowledge with broad potential in terms of applicability. Using patent citation data in four technological fields (energy production, automobiles, fuel and lighting), Dechezleprêtre et al. (2014) find that clean patents receive on average 43% more citations than dirty patents. Furthermore, the authors find that clean technologies receive on average more citations by highly-cited patents. They individuate two factors able to explain the clean superiority in terms of spillovers and applicability: clean technologies have more general applications, and they are radically new compared to more incremental, dirty innovations.

In a similar vein, Quatraro and Scandura (2019) argue that green innovation is characterized by higher complexity and novelty. Comparing green and non-green patents applied at the EPO, they indeed show that, on average, GTs display higher values in the patent scope, originality, forward citations, generality and two OECD composite indicators of patent quality.

According to the recent strand of literature investigating the labor market implications associated with the transition towards green production systems, green occupations exhibit a stronger intensity of high-level cognitive skills compared to non-green jobs (Consoli et al., 2016; Vona et al., 2017, 2018). Furthermore, the extant empirical evidence suggests that occupations that are changing qualitatively (*i.e.* in terms of their skill content) have on average more formal education, more work experience and more on-the-job training relative to non-green jobs (Consoli et al., 2016). Orsatti et al. (2018) conduct an aggregate analysis at the US commuting zone level about the effect of green public procurement and local skill compositions on the generation of GTs for the period 2000-2011. According to the authors, increasing public demand for green products and services leads to higher rates of green innovation, especially in areas where the concentration of high-skill occupations is higher.

Due to the characteristics associated with green innovation processes, public R&D is a natural candidate as a lever for green knowledge diffusion. The prior that public R&D points to more basic research is indeed common in the literature. In fact, in a competitive market setting, the amount of basic research generated is likely to be sub-optimal (Nelson, 1959; Arrow, 1962). This is due to the intrinsic features of basic research: the quantification of its economic value and the large number of externalities it generates. The former feature is due to the fundamental uncertainty characterizing the outcomes of basic research. Importantly, even when scientific discoveries occur, the timing in the realization of economic payoffs is strongly uncertain. Second, discoveries that stem from basic research tend to produce large and dispersed knowledge externalities: results and applications may be performed that are distant, both physically and technologically, from those that were expected ex ante. Hence, they may a) benefit several economic agents that are unconnected to those that provided the primary investments, and b) may open research trajectories in scientific branches previously loosely connected. As a consequence, social returns to basic research are typically larger than private returns, forcing the public sector to constantly and massively intervene.

Relevant to our analysis is that the nature of GT processes and the features characterizing basic research show large commonalities. Indeed, green knowledge shares with basic research the strong uncertainty related to both the rate of attainment and the time required for the realization of the relative economic payoffs. Furthermore, due to the global impacts of local environmental deterioration, positive spillovers from green-oriented interventions are very likely to spread in areas that are distant from the place where primary investments have been performed. Lastly, solutions to environmental issues may work for heterogeneous technologies in similar ways, making green knowledge largely applicable across sectors. These peculiarities make green knowledge close to basic knowledge. Publicly-funded R&D is thus a natural candidate for carrying out a more than compensatory role for green knowledge diffusion. Indeed, empirical studies largely demonstrate that the knowledge content of innovations resulting from public research is more general in its purpose and applicability, constituting the foundation of further scientific and industrial broad applications (Trajtenberg et al., 1997).

The combination of the characteristics of green innovation processes and publicly conducted R&D leads to the following hypotheses on the direction of green knowledge diffusion:

H2: *Increasing public R&D enhances the use of green knowledge by traditional technological processes.*

H3: *Increasing public R&D enhances the technological distance between green technologies and technologies using green knowledge.*

3 Methods

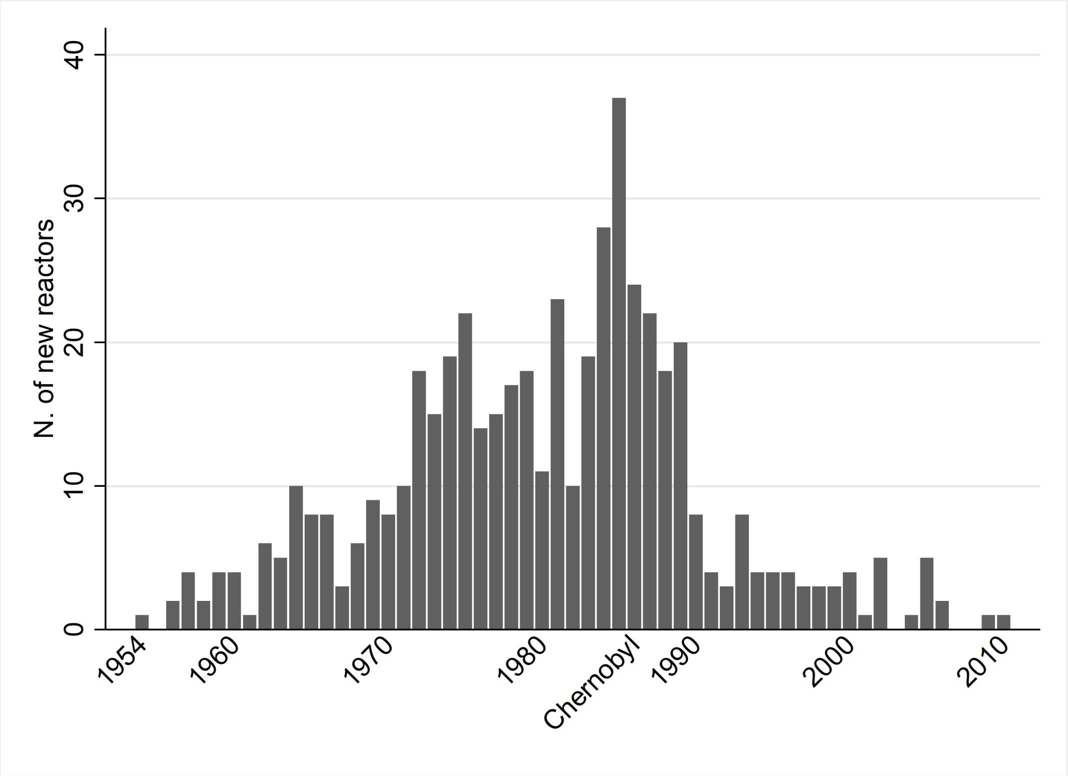
3.1 Research design and identification strategy

The aim of the paper is to estimate the causal effect of changes in public R&D on the diffusion of green technological knowledge. When it comes to investigate this relationship, several endogeneity problems emerge, related to both unobservable factors and reverse causality.

For what concerns potential omitted variables, both policy decisions and innovation are affected by the quality of the local institutional context and by human capital features, which are hard to measure appropriately.

For what concerns reverse causality in explaining the relationship between public policies and innovation outcomes, the established level of deployed technologies should be relevant in designing an innovation-oriented policy measure. Moreover, the more developed is an industry, the higher its contribution to total employment and value added generated, with reverse effects on policy decision-making processes. Thus, technology pulls policy intervention through several channels.

Figure 1: 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.

To overcome these endogeneity issues, we rely on the unexpected occurrence of the Chernobyl nuclear accident in 1986 as an exogenous shock impacting the policy architecture of the energy industry.

3.1.1 The energy sector in the 1970s and 1980s

The energy sector experienced a durable reconfiguration in the decades of the '70s and the '80s of the last century, 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, Figure 1 plots the number of new nuclear reactors connected worldwide to the grid by commercial operation year, during 1954-2010. The upsurge is continuous almost since the beginning of the series, increasing during the 1970s and reaching an impressive 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 Figure 2).[5] Conversely, the share of electricity production from fossil fuels (oil, gas and coal) fell from about 70% to about 50% in the same period for European countries. The US

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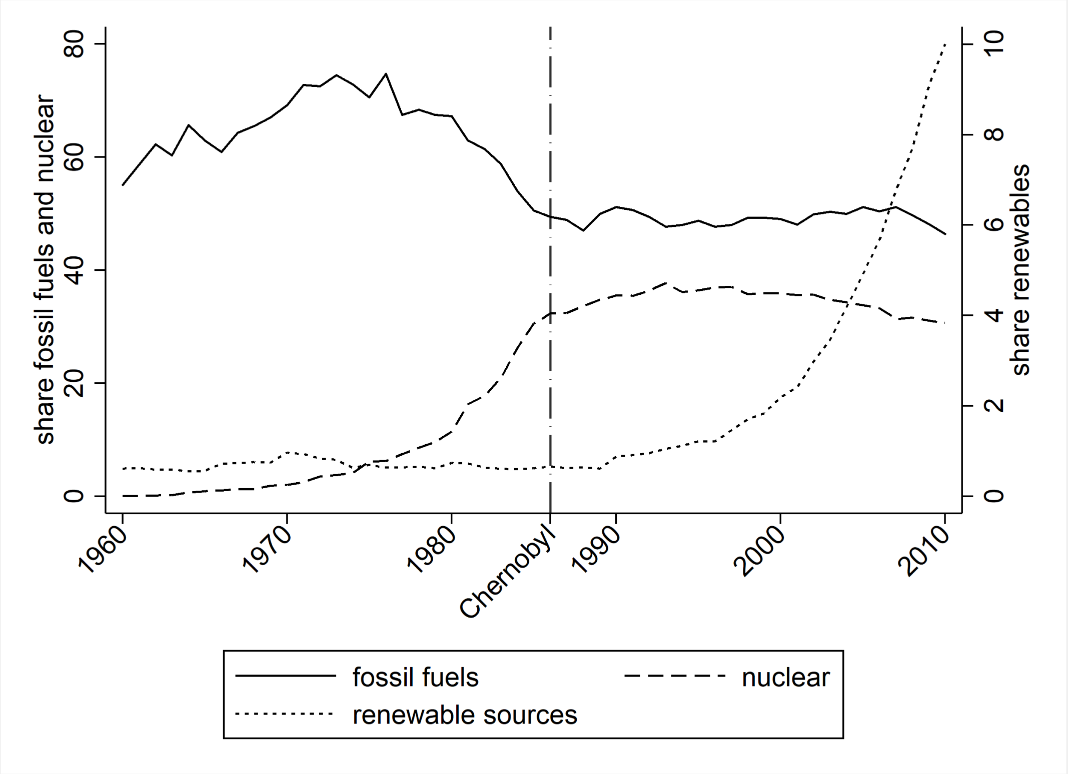
[5] Fossil fuel combustion is responsible for approximately 65 percent of global greenhouse gas emissions (US Environmental Protection Agency). Of these emissions, coal contributes for 45%, oil for 35% and natural gas for 20% (Carbon Dioxide Information Analysis Center). The major sectors demanding fossil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

FIGURE 2: ELECTRICITY PRODUCTION BY SOURCE, SHARES (EU, 1960-2010)



Notes: The figure plots the share contribution of the three energy sources (fossil fuels, nuclear and renewables) to electricity production in EU countries between 1960 and 2010. The hydroelectric source is not considered. *Source*: Author's elaboration on World Bank (2017) data.

experienced very similar patterns.

As for renewable sources (*i.e.* solar and wind), a public push for their development started in the late 1970s. The world 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 (Figure 2), 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 sort of almost 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.[6] Importantly, our main claim is that the entire policy architecture to limit the dependence from fossil fuel sources was based on the strong support to the nuclear source. Therefore, the development of renewable sources strongly relied on the success of nuclear programs.

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 sustainability and 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

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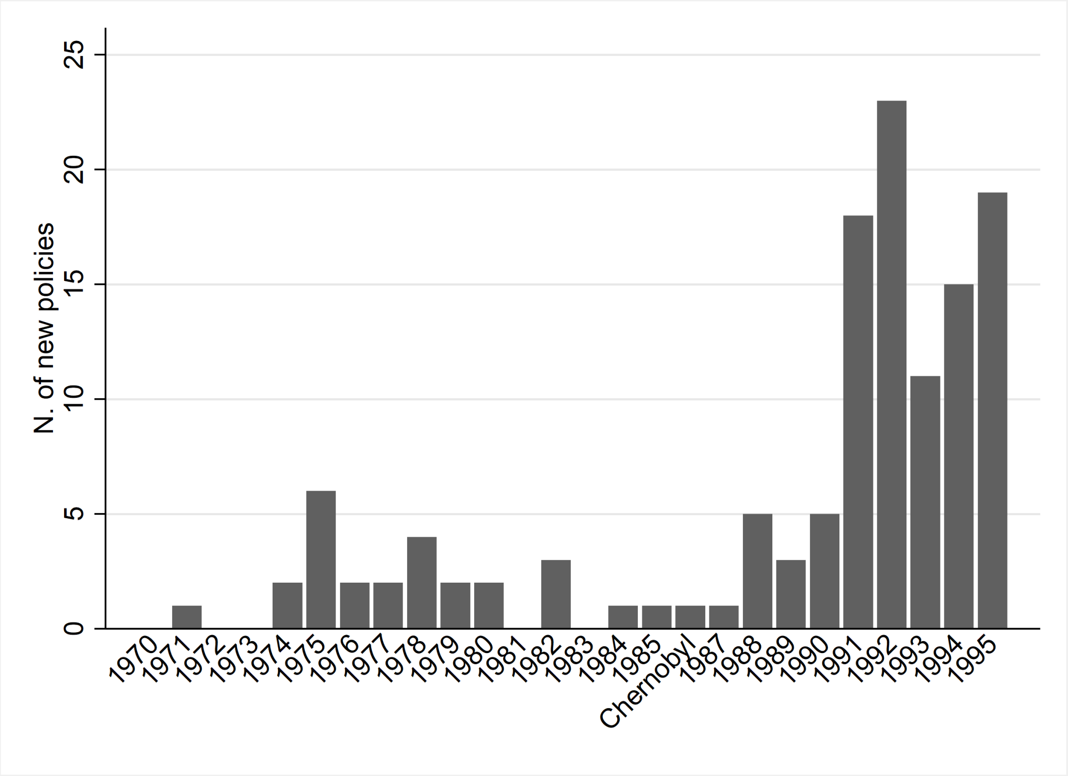
[6] Figure 3 plots the number of new policy tools implemented by IEA countries since the early 1970s. A first wave of policy intervention was concentrated between 1974 and 1980. Then, during the 1980s the effort sensibly reduced. A decisive policy boost finally started since the early 1990s.

Figure 3: 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 between 1970 and 1995. *Source*: Author's elaboration on IEA (2017) data.

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 was one of the countries that more strongly replied to the accident. After the 1987 *ad hoc* referendum, the Italian government decided indeed to phase-out its nuclear power activity, definitively shutting down its operative plants.

Summing up, the main hypothesis we draw is that the entire policy architecture for boosting alternative-to-fossil-fuel technologies has been exogenously affected by the Chernobyl accident, negatively. Figure 4 plots the pattern of the average government spending for R&D in energy vs. industrial production fields 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 do not show remarkable differences during the period 1982-1985, since 1986 an evident gap opens, with energy-related expenditures visibly declining, while public R&D for other industrial production projects continue increasing.[7]

Unfortunately, the available data on aggregate government R&D expenditures from 1980 to 1990 allow for disentangling between green and non-green targets only in the energy field, making im-

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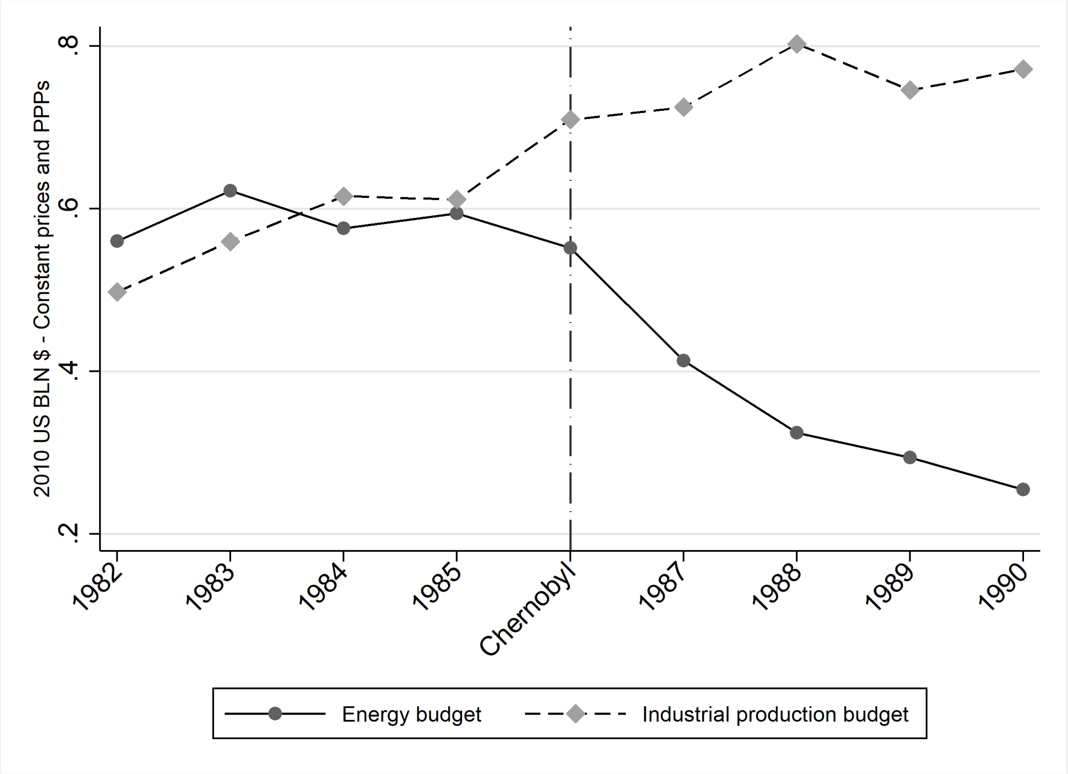
[7] Dooley (1998) found that most IEA member states reduced public energy R&D expenditures from the mid-1980s to the 1990s. He argues that this decrease is mainly due to deregulation of the energy markets, and that the remaining R&D money was shifted towards short-term, less risky research projects. 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. This drop was mainly due to, we argue, the policy reaction to the Chernobyl nuclear accident.

FIGURE 4: 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 and industrial production-related GBAORD (dashed line) in selected EU countries between 1982-1990. *Source*: Author's elaboration on OECD (2017) data.

possible to compare this pattern with the ones experienced by other domains. Exploiting energy data as a further descriptive support for the arguments proposed above, Figure 5 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. This evidence allows us to assume that, in relative terms, the fall in public R&D due to the Chernobyl accident was mainly driven by reducing public resources to alternative to fossil fuel technologies.[8]

3.1.2 Identification strategy

The arguments proposed above allow us to investigate the causal effect of changes in public R&D on the diffusion of green knowledge. In fact, we can exploit variation across time and technological domains to instrument the level of public R&D.

Anticipating the next subsection, we conduct our analysis at the patent level. Precisely, we collect information on green patents applied at European Patent Office between 1980 and 1984. Each green patent is assigned to a technological field that, in turns, is linked to specific public R&D.

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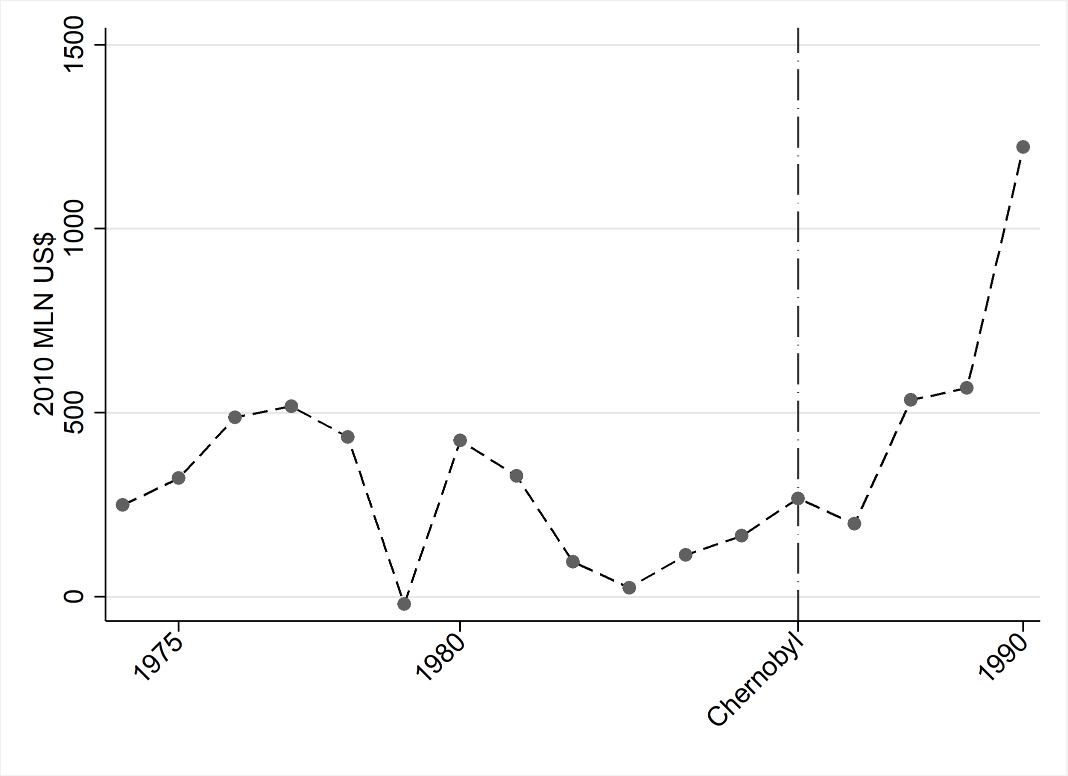
[8] It must be stressed that a sharp decline in public R&D for energy technologies in the US started since the early 1980s (Margolis and Kammen, 1999). Therefore, in a robustness check discussed in Section 4.4 we exclude US invented patents from the sample. Results confirm the main analysis.

Figure 5: 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 renewable sources between 1974 and 1990. *Source*: Author's elaboration on OECD/IEA (2017) data.

The time at which public 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 public R&D in the energy domain was affected by the Chernobyl accident. The level of public R&D in the energy domain before the Chernobyl event and the level of public R&D in other domains before and after the Chernobyl event were not affected. Therefore, we can combine differences in public 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 can be used as an instrument for the level of public R&D.

If the Chernobyl accident exogenously forced governments to reduce public R&D 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 public R&D expenditures, while controlling for energy field and cohort effects. This difference-in-differences (DiD) specification controls for overall time trends in public R&D (across all green technologies) and for time invariant unobserved differences between technological fields (Angrist and 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 would not have been systematically different between energy and non-energy green domains. Figure 4 already suggests that this was the case. However, to provide robust evidence of the validity of this assumption for our sample, we formally test for the absence of pre-trends in the level of public R&D across technological domains, as described and discussed in Sections 3.4 and **??**.

3.2 Data and sample

We study the effect of a change in public R&D on the level and the qualitative characteristics of the citation flow to GTs exploiting information contained in patent citation data. Precisely, we select green patents applied at the European Patent Office (EPO) between 1980 and 1984 by inventor residing in 16 OECD countries as our unit of analysis.[9]

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,[10] 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.[11] We combine both classifications to individuate green patents, excluding from the classifications nuclear power-related patents.

The resulting sample consists of 16,091 unique green patents. Of them, 1,631 are related to the energy field (10.14%). Patent citations for this set of patents have been collected for the period 1981-1988 included.[12]

3.3 Variables

3.3.1 Dependent variables

Green knowledge diffusion is measured through the number of citations received by green patents. The number of citations a patent receives reveals that the knowledge incorporated in the protected technology is somehow subsequently used by innovating and producing companies (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 knowledge is used by further innovation processes. Due to this reason, citations are a good proxy for knowledge diffusion.[13] Citations are corrected for DOCDB patent families to account for the entire flow of citations a specific

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[9] OECD countries considered are: Australia, Austria, Belgium, Canada, Switzerland, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, the UK and the US.

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

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

[12] We decide to 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 our study.

[13] 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 and Trajtenberg 1999; Maurseth and Verspagen 2002; Bottazzi and Peri 2003; Bacchiocchi and 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).

technology receives.[14]

As for the second and third step of the analysis, we estimate the effect of a change in the level of public R&D on, alternatively: *a)* the number of citations from non-green patents; and *b)* the average technological distance of the citing patents.

For GTs to impose, a crucial feature is the hybridization of traditional technological processes (Zeppini and van den Bergh, 2011). Due to its nature, we argue that public R&D is a lever for green knowledge to diffuse across traditional domains. To test this hypothesis, we estimate the effect of changes in the level of public R&D on the number of citations from traditional, non-green patents.

Finally, we test the hypothesis that public R&D also fosters the use of green knowledge by distant technologies. To build a measure of technological distance between patents we 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). Our 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 our focal green (cited) patents, we calculate $d(i,j)$ for all the IPC pairs formed by citing IPC classes and IPC classes contained in the focal patents. For each focal patent i at time t, we then take the average technological distance from its citing patents as our dependent variable.[15]

3.3.2 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. Essentially, this involves identifying all the 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.[16] They include R&D performed on the national territory as well as payments

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[14] 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 Martínez (2011).

[15] To build our measure of technological distance we consider all the patents applied at EPO during 1980-1988 that cited at least one EPO patent.

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

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 we follow two steps. According to Stančík (2012), we assign SEOs to economic sectors (NACE rev. 2 sectors). Then, according to Van Looy et al. (2014), we assign NACE codes to IPC classes. This two step matching procedure allows us to measure the level of GBAORD related to each technology classifying a patent, differentiating between the energy domain and the rest.[17,18]

Control variables include a binary variable for energy patents[19] 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, we also include additional time-varying controls. First, we 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; the country emission intensity, as a control for the overall country environmental policy effort that indirectly fosters innovation in GTs;[20] finally, we also add the (log transformed) level of oil price, adjusted for inflation, as a 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 and Urpelainen, 2012). Table 1 provides summary statistics of the variables considered.[21]

3.4 Empirical models

To measure the effect of a change in GBAORD on the rate and the direction of green knowledge diffusion, we estimate three specifications of a two-stage least square model (2SLS). In the first stage (which is common to all three specifications), we estimate the level of GBAORD with a linear probability model in a DiD configuration. Precisely, we include the interaction between the energy

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[17] Unfortunately, we are not able to measure the exact level of government R&D funding assigned to the green subcategory for each observed field. Therefore, we can only estimate the effect of aggregate public R&D expenditures on green knowledge diffusion. Under the assumption that the composition of the funding (green vs. non-green) does not differ between technological domains, the overall level of R&D allows us to capture variability in terms of public (green) R&D intervention across domains.

[18] Field-specific GBAORD is measured at the country level. Patents are assigned to countries according to the inventor's country of residence.

[19] The coefficient of the binary variable for energy patents is dropped when we specify our empirical models including patent fixed effects.

[20] 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. We therefore exclude patents invented in Germany from our main analysis. However, in a robustness check we consider also those patents, omitting emission intensity from the control variables. Results are consistent with the main analysis and are reported in Table 5. Alternatively we 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, micro-organisms) 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. We thus use this kind of expenditure as a further control for the overall public policy pressure. However, since we can not rule out the possibility that this kind of R&D targets specific GTs, we use this measure only in robustness analyses. Results do not change when it is included and are reported in Table 5.

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

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

Notes: Please see the text for details on variable construction.

domain dummy and the cohort indicator ($ENERGY_i \times POST_{i,t}$, whose effect is captured by the coefficient β_2) as the exogenous variable capturing the causal effect of the shock due to the Chernobyl nuclear accident, the post-Chernobyl period indicator ($POST_{i,t}$), patent and year fixed effects (α_i and δ_t, respectively), and time-varying control variables described in Section 3.3.2 ($\mathbf{\Omega'_{i,t}}$).[22] Formally, the first stage takes the following form:

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

After instrumented, we estimate the effect of changes in the level of GBAORD on the three outcomes of interest.[23] The second stage takes the following form:

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

where $Y_{i,t}$ is, alternatively, *i)* the total number of citations received by patent i at time t, *ii)* the number of citations received by patent i at time t, coming from non-green patents, or *iii)* the average technological distance of citations received by patent i at time t; α_i are patent fixed effects; δ_t are year fixed effects; $POST_{i,t}$ is the post Chernobyl period indicator; $\widehat{GBAORD}_{i,t}$ is the (instrumented) level of GBAORD affecting patent i at time t; the vector $\mathbf{\Omega'_{i,t}}$ contains the set of time varying controls, as described in Section 3.3.2; $\epsilon_{i,t}$ is the error term.

As stressed in Section 3.1.2, 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, we test for Chernobyl pre-trends in the level of GBAOD by looking at the full set of lags and leads around the time of the nuclear accident ($k = -3, ..., 2$; excluding -1) for energy and non-energy patents (L_{ik}). We 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 public 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; we include a period event dummy $Post_{it}$ that is equal to 1 post Chernobyl event and is common to treated (energy related) and control (non-energy related) green patents (the predicted effect is captured by β^{All}); lastly, we

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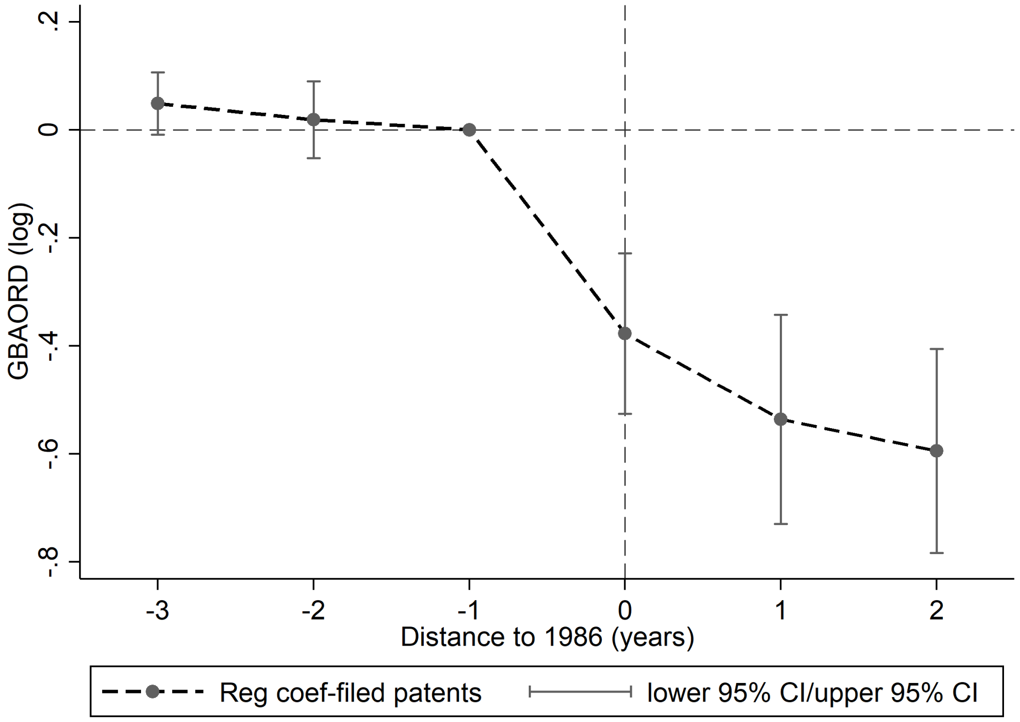
[22] Note that we drop the coefficient related to the dummy $ENERGY_i$ since we include patent fixed effects in the models.

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

FIGURE 6: THE EFFECT OF THE CHERNOBYL NUCLEAR ACCIDENT ON GBAORD



Notes: The figure reports point estimates of the dynamic effects associated with lags and leads around the Chernobyl accident (i.e., the set of β coefficients in the equation 4).

include also patent and period fixed effects (α_i and δ_t, respectively).[24]

4 Results

The purpose of the empirical analysis is to test for the effect of GBAORD on both the rate and the direction of green knowledge diffusion. To find causality going from changes in GBAORD to green knowledge diffusion, we frame the empirical analysis in an instrumental variable setting. Coherently, we 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 (Equation 2). After instrumented, we estimate the effect of a change in GBAORD on the three outcomes of interest (Equation 3). Before discussing the results of our analysis, we provide empirical evidence of the opportunity to exploit the occurrence of the 1986 Chernobyl nuclear accident to instrument the level of GBAORD.

4.1 Testing for dynamic effects of the Chernobyl 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 green domains.

To test for the absence of pre-trends in GBAORD across technological domains, we estimate the model specification described by Equation 4.

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[24] Note that periods refer to years 1983-1988. Therefore, period 0 is 1986.

Figure 6 reports the β coefficients which indicate the yearly level of GBAORD for energy-related green patents. We observe a relative strong decline since 1986, confirming that the Chernobyl nuclear accident induced a relevant reduction in energy-related GBAORD. The negative estimated effect increases over time, ranging between around -37% (in 1986) and -59% (in 1988).

This empirical setting allows us to formally test the hypothesis that point estimates are the same before and after the Chernobyl nuclear accident occurred in 1986. The null hypothesis is:

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

Results indicate that we cannot reject the hypothesis that the point estimates are all the same before 1986, but we can since 1986. Table 2 indicates indeed that there are no pre-trends but an effect on GBAORD in the year of the Chernobyl nuclear accident and in the two years after.

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

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

4.2 First stage results

We now turn to the results obtained from the first stage of the 2SLS models, whose specification is formalized by Equation 2.

As discussed above, we estimate a negative impact of the Chernobyl nuclear accident on the level of GBAORD in the years after the event. The average post Chernobyl negative effect (whose dynamics is estimated according to Equation 3 and reported in Figure 6) is estimated according to Equation 2 and reported in Table 3.

Column I reports the results when we only control for the post-Chernobyl indicator ($POST_{it}$), patent fixed effects and calendar year fixed effects. The magnitude of the coefficient for the interaction between $ENERGY_i$ and $POST_{it}$ (our DiD variable capturing exogenous variation in the level of GBAORD due to the Chernobyl shock) is -.40, meaning that GBAORD on average dropped by 40% as a consequence of the Chernobyl accident.

Columns II to IV report the results when we include, separately, the three main time varying control variables described in Section 3.3.2. Precisely, in column II we add *BERD*, in column III we add *Emission intensity*, while in column IV we add *Oil price*. Finally, column V reports the results when we saturate the model adding all the control variables (Equation 2). The coefficient of our interaction of interest ($ENERGY_i \times POST_{it}$) is stable in terms of both significance and magnitude across all the specifications. Finally, the F-statistics of excluded instruments are always above the threshold of 10, confirming that our instrument is not weak (Staiger and Stock, 1997).

Overall, the results from the first stage indicate that the natural experiment had a significant and strong negative effect on the level of GBAORD.

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

Notes: Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

4.3 Second stage results

We then estimate the effect of changes in GBAORD on our outcomes of interest. Second stage results are reported in Table 4. The first stage for the three estimated models is reported in Table 3, column V.

Our 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 the overall diffusion of green technological knowledge. Results show that the coefficient of GBAORD is positive and significant. Precisely, a 1% increase in GBAORD leads to around .066% increase in the number of citations received by green patents. The magnitude of the GBAORD coefficient might seem surprisingly small. However, it must be stressed that GBAORD captures the overall level of expenditures in public R&D. During the period 1981-1988 only a small amount of GBAORD targeted environmentally-related projects.[25] Therefore, it is reasonable to assume that only a tiny fraction of the 1% increase in GBAORD is responsible for the estimated .066% increase in overall citations to green patents. In other words, if the hypothetical 1% increase in GBAORD would entirely target green R&D projects, it is very likely that the positive effect on citations will be notably higher.

As for the control variables, the coefficient for $BERD$ is not significant. This result is reasonable, since BERD captures the level of private R&D that, at that time, was only peripherally related to green innovation (i.e., an increase in BERD is very unlikely to verify due to green R&D). As for $Emission\ intensity$, its coefficient is negative and significant, meaning that the lower the overall environmental policy pressure at the country level (i.e. high levels of emission intensity) the lower the level of green knowledge diffusion. Finally, the coefficient referring to $oil\ price$ is positive and significant, meaning that the diffusion of green knowledge positively responds to an increase in the cost of fossil fuels, as expected.

Overall, results reported in column I provide support to the first hypothesis stated in Section 2.1, according to which public R&D is an effective tool for more than attenuating the 'double externality' issue characterizing green innovation processes, therefore fostering the diffusion of green

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

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	0.16***	0.056***	0.0021***
	(0.021)	(0.015)	(0.000)
BERD (log)	-0.00036	-0.019	-0.0020***
	(0.021)	(0.015)	(0.001)
Emission intensity	-0.082***	-0.060***	-0.0080***
	(0.015)	(0.010)	(0.000)
Oil price (log)	0.14***	0.036**	-0.00049
	(0.020)	(0.015)	(0.000)
Patent FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	99,002	99,002	99,002

Notes: Robust standard errors are in parentheses. First stage reported in Table 3, column (V). * $p < .1$, ** $p < .05$, *** $p < .01$

technological knowledge.

We then enter more in depth into the understanding of the direction that green knowledge diffusion takes. In Table 4, column II we report the results when the dependent variable is the (log transformed) number of citations to green patents coming from non-green patents. The coefficient of $GBAORD$ is positive and significant, with a magnitude similar to the one estimated for the overall number of citations received by green patents (i.e. 0.07%). This result provides support to hypothesis 2: GBAORD fosters the diffusion of green knowledge in traditional domains, accelerating the process of technological hybridization.

The coefficients for the control variables are similar to the ones discussed above. The only remarkable difference is for the variable *oil price*, whose coefficient is sensibly lower than the one reported in column I. This suggests that the increase in the cost of using fossil fuels is more likely to foster substitution than conversion of traditional technologies.

Finally, in column III we report the estimates of the effect of $GBAORD$ on the average technological distance of patents citing GTs (hipothesis 3). Also in this case the coefficient of $GBAORD$ is positive and significant, meaning that public R&D fosters the diffusion of green knowledge in technological domains that were previously loosely related to GTs. Precisely, a 1% increase in GBAORD leads to some .008 increase in the technological distance index described in Section 3.3.1.

As for the control variables, the coefficients for both $BERD$ and *Emission intensity* show significant and negative signs. The interpretation of the former coefficient likely deals with path dependence in innovation processes (i.e. R&D expenditures tend to be directed towards specialization, this reduces the average technological distance between new and older innovation processes), while the interpretation of the latter adds an interesting insight to what stressed when commenting its effect on the number of citations to green patents: a low level of environmental policy pressure does not just block green knowledge diffusion but reduces also the average technological distance of inventions making use of green knowledge, possibly creating harmful consequences in terms of overall technological diversification. Finally, *oil price* does not show a significant coefficient.

TABLE 5: INCLUSION OF GERMANY-INVENTED PATENTS

PANEL A: FIRST STAGE RESULTS

	Exclusion Emission Intensity	Inclusion GBAORD Env
	Dependent variable: GBAORD (log)	
	(a)	(b)
Energy × Post	-0.487***	-0.491***
	(0.0035)	(0.0038)
Controls	YES	YES
Patent FE	YES	YES
Year FE	YES	YES
Observations	146,483	146,483
Adjusted R^2	0.290	0.311
F-stat	25.23	25.29

PANEL B: SECOND STAGE RESULTS

	Dependent variables:					
	Tot cits (log)	Dirty cits (log)	Tech distance	Tot cits (log)	Dirty cits (log)	Tech distance
	(a.I)	(a.II)	(a.III)	(b.I)	(b.II)	(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	146483

Notes: Panel A reports the first stage results. Column (a) excludes Emission Intensity from the set of control variables; column (b) substitutes Emission Intensity with GBAORD related to the environment (GBAORD env). Panel B reports the second stage results. Columns a.I, a.II and a.III are based on the first stage reported in Panel A, column a. Columns b.I, b.II and b.III are based on the first stage reported in Panel A, column b. All the models are estimated on the sample used in the main analysis, extended also to patents invented in Germany over the period 1980-1984. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

4.4 Robustness checks

Germany invented patents As stressed in footnote 19, the World Bank database does not provide data on emission intensity for Germany before 1991. We therefore exclude patents invented in Germany from our main analysis. However, here we provide a set of robustness checks including also those patents in the sample. To do so, in a first set of estimates we remove *Emission Intensity* from the control variables. Moreover, we also provide further robustness evidence substituting the (log transformed) level of GBAORD targeting the environment (*GBAORD env*) for *Emission Intensity*. Results are reported in Table 5. Panel A 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 B 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 of the citations received. Columns a.I, a.II and a.III are based on the first stage reported in Panel A, column (a). Columns b.I, b.II and b.III are based on the first stage reported in Panel A, column (b).

Overall, results confirm the main findings reported in Table 3 and in Table 4. Looking at the first stage (Panel A), 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 outcome of interest (Panel B), we find significant positive coefficients, whose magnitudes are slightly lower than what found for the main sample (i.e., comparing Table 5, Panel B with Table 4). Precisely, the estimated coefficient for GBAORD when the dependent variable is the total number of citations reduces 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 reduces from .070 to .057 (column a.II). Finally, also the impact of GBAORD on the average technological distance of patents citing green patents diminishes from .008 to .006. Those coefficients are fully stable when *GBAORD Env* enters the set of control variables (columns b.I, b.II and b.III).

Table 6: Exclusion of US- and UK-invented patents

	PANEL A: FIRST STAGE RESULTS Dependent variable: GBAORD (log) (I)
Energy × Post	-0.614***
	(0.0073)
Controls	YES
Patent FE	YES
Year FE	YES
Observations	36,724
Adj. R^2	0.427
F-stat	16.17

PANEL B: 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

Notes: Panel A reports the first stage results. Panel B reports the second stage results. Columns I, II and III are based on the first stage reported in Panel A. All the models are estimated on the sample used in the main analysis, reduced by excluding patents invented in the US and in the UK. Robust standard errors are in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$

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 and

Kammen, 1999). During the 1980s, similar policy interventions were implemented also in the UK. Therefore, we exclude both US- and UK-invented patents from the analysis as a further robustness check. Results from this reduced sample of patents are reported in Table 6 and largely confirm the main findings discussed in Sections 4.2 and 4.3. Looking at the first stage (Panel A), the estimated negative impact of the Chernobyl accident on the level of GBAORD is the largest we estimate in our empirical analysis, reaching -61.4%. As for the second stage results (Panel B), we find significant positive coefficients, whose magnitudes are slightly lower than what found for the main sample. Precisely, the estimated coefficient for GBAORD when the dependent variable is the total number of citations reduces from .066 to .058 (column I). Similarly, when the dependent variable is the number of citations from non-green patents, the coefficient of GBAORD reduces from .070 to .049 (column II). Finally, also the impact of GBAORD on the average technological distance of patents citing green patents diminishes from .008 to .005 (column III).

5 Conclusions

Simultaneously fostering the emergence of breakthrough green technologies and substituting traditional emitting technologies with existent clean ones are crucial policy targets for guaranteeing long-run growth. Given the level of advance of traditional technologies and the cumulative nature of innovation processes, supply side (public) interventions are indispensable for filling the technological gap between environmentally friendly and traditional technologies.

The present paper aims at contributing the literature on policy-driven green technical change by providing evidence of the causal effect of changes in public R&D on both the rate and the direction of green technological diffusion. Understanding diffusion dynamics of green knowledge as a response to public R&D is indeed relevant for a better design of the policy architecture targeting green growth.

By investigating citations to green patents filed at the EPO during the period 1980-1984, results reveal a significant positive effect of increasing public R&D on the overall process of green technological knowledge diffusion. Therefore, public R&D has not only the expected effect of compensating for the lack of private incentives in investing in green innovation activities but, importantly, it also fosters knowledge spillovers from green technologies. 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.

Moreover, 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 also be directed towards traditional processes with the highest probability of being efficiently hybridized.

Finally, we also empirically document the positive role of public R&D in enlarging the spectrum of invention processes making use of green knowledge. Fostering knowledge spillovers towards heterogeneous domains is likely to benefit systemic technological dynamism, reducing the risks associated with possible technological lock-ins and, moreover, creating new opportunities of technological hybridization.

The main policy implication of this study is that governments should promptly shift public

R&D resources from dirty to green technological targets to significantly accelerate the diffusion of green knowledge, both within the green domain and across heterogeneous and distant technological areas. This is likely to reduce the time required by green technologies to overcome the technological advantage of traditional innovation processes, fostering both substitution and hybridization, and to benefit economic growth also in the short run.

As for future research, a finer systematic investigation is required to individuate technological R&D niches with the highest breakthrough potential to be systematically targeted by public R&D projects. Directing public R&D investments towards more promising inventive areas is indeed likely to speed-up green knowledge diffusion. At the same time, the management of public R&D projects is a topic that deserves immediate academic and policy attention. Finally, the coordination between public and private R&D investments in green innovation processes necessarily complements this discussion.

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