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Walking the Green Line: Government Sponsored R&D and Clean Technologies

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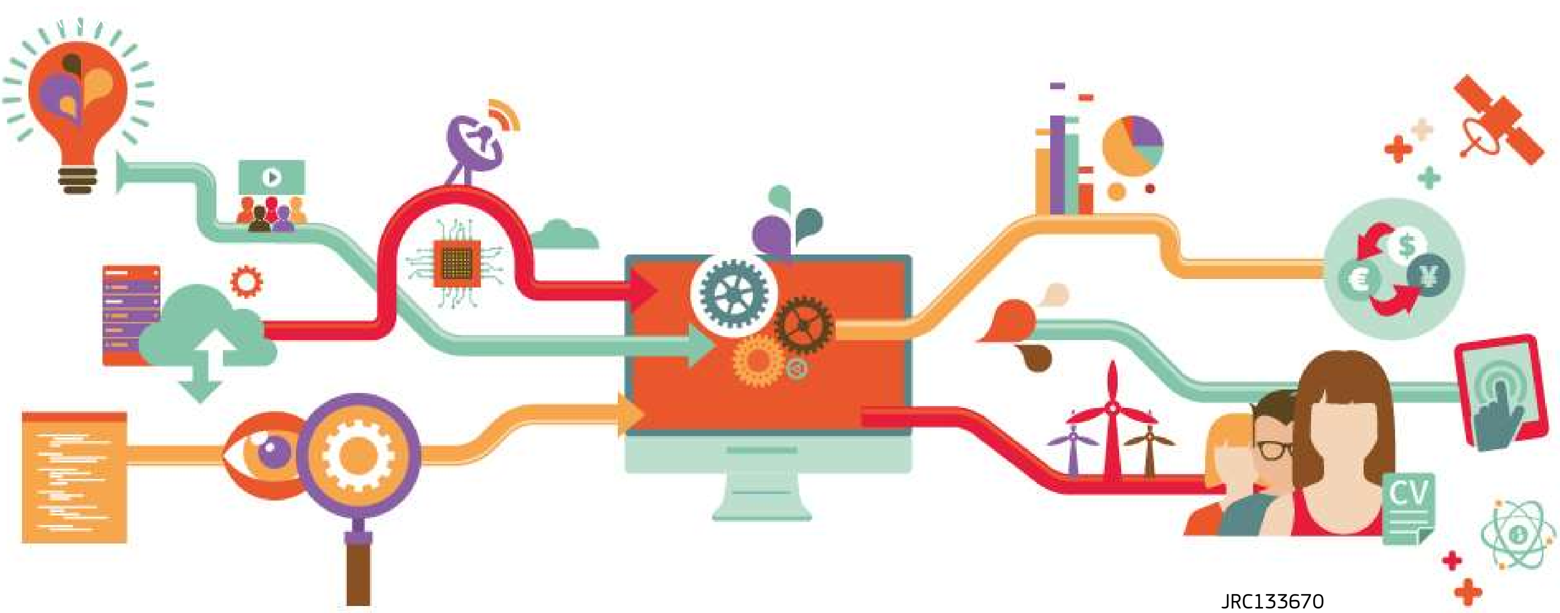

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Abstract

We examine whether government sponsored R&D induces the development of clean technologies with a high impact on subsequent technological development. The analysis uses information on USPTO patents granted between 2005 and 2015 and combines different methods to control for possible sorting of projects into public funding and for non-random (public) treatment. We also assess the distributional effect of government sponsored R&D. Results show that patents from public funded projects have a significantly higher impact and that this is particularly true for highly cited patents, thus supporting a role for technology-push policies in determining a clean technological transition.

Executive summary

This work presents a critical analysis of the role of public policy in the development and adoption of clean technologies, particularly the influence of government-sponsored Research and Development (R&D) programs. The study aims to provide empirical evidence of the effect of public R&D policies on advancing clean technologies with substantial knowledge spillovers.

Despite the global commitment to reduce greenhouse gas emissions, the level of public support for clean technologies has been inconsistent across OECD countries since 2011. The development of clean technologies has stagnated, and the private sector's incentive to innovate in this area seems to have decreased. This calls for a reassessment of the effectiveness of R&D policies in promoting the development of clean technologies.

The work underscores the need for public action in the economics of climate change. Market-based policies, such as carbon-tax, are not enough as they fail to internalise the long-term benefits of superior, clean technologies. Therefore, R&D subsidies are necessary to redirect innovation from dirty to clean technologies.

The study posits that science-push policies, such as public R&D, are expected to have a profound impact on new clean technologies due to their novelty and role as foundational elements for subsequent technological advancements. Public R&D is crucial in promoting the development of high-impact clean technologies, which form the basis of a new technological paradigm.

In our empirical investigation, we use patents granted by the USPTO between 2005 and 2015 linked to procurement contracts or research grants with a US funding agency to examine the effect of technology-push policy. The results reveal a significant impact of government-supported clean technologies on subsequent innovations, with supported technologies receiving about 26% more citations than non-supported ones within a 5-year period. This effect was noted among clean technologies with the highest impact on subsequent technological development.

This analysis provides two significant implications:

- Climate change policy modelling should acknowledge the potential influence of policies on the knowledge spillovers of technologies rather than treating them as exogenous.
- In the implementation of climate change policies, R&D support should accompany standard market pull interventions to expedite technical change towards sustainable growth. This argument provides a rationale for reversing the declining trend in technology support policies observed in OECD countries since 2011.

In conclusion, this work highlights the critical role of government-sponsored R&D in fostering impactful clean technologies. The findings provide a compelling argument for policy makers to reinforce their R&D programs to achieve sustainable growth and mitigate climate change.

1 Introduction

The reduction of greenhouse gas emissions is the most important mean to mitigate climate change (IPCC, 2022). Innovation policy packages have enabled cost reductions and supported global adoption of low-emission technologies. However, an important part of emission reduction will depend on new clean technologies that are still embryonic and marked by high technological and market uncertainty (IEA, 2021). This represents an obstacle to private initiatives and makes the support of public policy crucial for their development. To this end, some governments have reinforced their Research and Development (R&D) programs to foster environmental innovation, like in the US with the ARPA-E scheme and in the EU with the Innovation Fund.

Nevertheless, the public support to clean technologies is less systematic than it may appear. Across the OECD, from 2011 the (stringency) level of technology support policies has declined until 2016 and has then experienced a scattered increase, but without reaching the 2011-peak (Kruse et al., 2022). This has occurred while the development of clean technologies, as revealed by environmental patents, has stopped growing and embarked along a continuous slow down until the most recent years (Dechezleprêtre and Kruse, 2022; IEA, 2020). Private incentives to develop new clean technologies might have decreased and evidence about the effectiveness of R&D policies in restoring them is thus needed to justify their budgeting.

The relevance of public action is a well-recognised intrinsic feature of the economics of climate change (Stern, 2008; Nordhaus, 2019). Among the different leverages, the role of public support to R&D has been less scrutinized compared to market-based and regulatory approaches. Despite its ascertained role in directing technical change towards sustainable growth, a gap remains about the strength of public R&D in playing this role: does it facilitate environmental innovations that act as steppingstones to subsequent technological developments?

From a theoretical point of view, a recent stream of endogenous growth models applied to the environment have shown that policy is crucial for the development of clean technologies, given the path-dependent nature of technical change (Acemoglu et al., 2012; 2016; Hémous and Olsen, 2021). A sole market-based policy, such as carbon-tax, is not enough (Acemoglu et al., 2012). As the market keeps on allocating resources to innovation by looking at immediate profits, without retaining the discounted benefits that superior technologies will bring over the long run, the dirty technology sector may remain the first best allocation for incumbents even with a carbon tax. In order to redirect innovation from dirty to clean technologies, R&D subsidies are needed to make the market internalise the higher returns, private and social, of clean technologies in the long run.

Following the same background, science-push policies like public R&D can be expected to have a deeper impact on new clean technologies, related to their novelty and their role as basic components for subsequent technological development (Trajtenberg et al., 1997). Unlike market-pull policies, which act on private incentives in the short run, science-push policies increase the expected social value of clean technologies, whose time horizon is longer and provide inventors with incentives to work on more radical innovations. Similarly to what has been found for other technologies (Acemoglu and Linn, 2004; Dranove et al., 2020; Dubois et al., 2015; Finkelstein, 2004), public R&D is arguably needed to spur the development of high impact clean technologies, which represent basic steppingstones in the unfolding of a new technological paradigm. Despite the intuition behind this argument, its supporting theoretical mechanisms have not been fully addressed yet. Furthermore, the extent to which this specific impact of R&D policy actually happens still lacks systematic empirical evidence.

To fill this gap, we examine whether government sponsored R&D facilitates the development of clean technologies with large knowledge spillovers on subsequent innovations. Given the path-dependency that characterises technical change (Acemoglu et al., 2012), an important part of the policy impact in fact passes through the (knowledge) value that newly developed green technologies have for the development of subsequent ones. Consistently with the path-dependency hypothesis, should policy induced clean technologies be marked by larger spillovers, they could foster the diffusion of clean knowledge through their influence on subsequent technological developments.

We do expect this to happen by referring to firms' decisions to invest in radically new research projects (Azoulay et al., 2019), which yield innovative outcomes of high impact in terms of knowledge spillovers. These projects are typically risky and early-stage, and are thus marked by marginal costs that overcome their marginal benefits to a larger extent than lower impact projects. This is due to different mechanisms. To start with, high impact innovative outcomes increase the risk of being imitated and this stimulates the innovator to delay their realisation over time (Mukherjee and Pennings, 2004). Furthermore, having a larger impact naturally increases the externalities that early innovators can dynamically have on later innovators, decreasing the returns that the former can appropriate and thus the incentives to undertake the relative investment (Scotchmer, 1991). For these reasons, firms generally find unprofitable to invest in high impact projects and their realisation is thus crucially linked to the public support. By the same token, the marginal technology that government sponsored R&D supports, can be expected to have higher knowledge spillovers than non-supported ones.

This differential effect has been found by Azoulay et al. (2019) looking at the impact of scientific grants on firms' patenting in the pharmaceutical and biotechnology industries. The underlying mechanisms leading to their results are expected to hold also with respect to clean technologies. These are technologies whose development relies on the combination of more diverse and novel technological components than non-clean ones, and which thus require a larger and more uncertain cognitive effort (Barbieri et al., 2020). Furthermore, investments in clean technologies have been proved to yield positive returns to firms only in the presence of high energy costs, thus increasing their market uncertainty (Popp, 2002). This further constrains the incentives for firms to invest in new, high-impact clean technologies. Such technologies, arguably, are more likely to receive support from government-sponsored R&D.

We investigate the extent to which this is actually the case, by filling a gap in the empirical research about the development of clean technologies, mainly focused on environmental policies that act on the (private) market side, like: shocks inducing changes in energy prices (Noailly and Smeets, 2015; Hassler et al., 2021), emission trading systems (Calel and Dechezleprêtre 2016), changes in emission standards (Rozendaal and Vollebergh, 2021), international environmental agreements (Dugoua, 2021), and carbon and environmental taxes (Aghion et al., 2016). Empirical analyses of R&D policies are instead more scattered. With respect to the automobile industry, Aghion et al. (2016) showed that temporary R&D subsidies designed to increase energy efficiency can favour the development of incremental clean (grey) innovations, while radically clean innovations remain unaffected. Working on the R&D grants issued by the US Department of Energy, Howell (2017) shows that recipient small businesses in clean energy sectors increase their patenting, VC financing, and survival rate, while these effects are non-significant in conventional (dirty) energy technologies like natural gas and coal. Additional evidence regarding the impact of other types of technology support policies, particularly those focusing on demand-side strategies such as public green procurement, is limited and primarily found in a few select works (Ghisetti 2017; Krieger and Zipperer, 2022).

We add to this stream of empirical research focusing on government sponsored R&D in the US and provide evidence of its role in fostering the development of clean technologies with a high impact on subsequent innovations. We rely on patents granted at the USPTO between 2005 and 2015 to applicants linked to at least one procurement contract or research grant with a US funding agency, and investigate the impact of technology-push policy through a quasi-experimental estimation framework.

Using citations from other patents to proxy the impact on subsequent technological development, we show that the effect is remarkable in size: in a 5-years window government supported clean technologies have about 26% more citations than non-supported ones. The size of the effect remains sizeable also when we further disentangle citations to consider different types of knowledge spillovers, entailing gradually more stringent channels of diffusion. The knowledge spillovers generated by government supported clean technologies do not appear less (or more) localized within the US than privately funded ones but they have a higher geographical scope, pertaining to technologies developed by applicants from a larger basket of countries. We also uncover the distributional effect of government R&D support, which increases along the distribution of citations and is significant only among those clean technologies with the highest impact on subsequent technological development. The results are robust to a battery of robustness checks that we have implemented to validate the effect of government R&D support on the knowledge spillovers of clean technologies.

Our results have two immediate implications. First, they suggest that the modelling of climate change policies should overcome the assumption that knowledge spillovers of technologies can be treated as exogenous. Not only policies can support the development of clean technologies with larger spillovers than dirty ones as showed by Dechezleprêtre et al. (2017); technology-push policies increase the spillovers also among clean technologies, with implications on how R&D investments and learning-by-doing should be modeled.

Second, in the undertaking of climate change policy, our results suggest that an R&D support should accompany more standard market pull interventions, not only to direct technical change towards more sustainable growth patterns, but also to foster the speed of technical change along the same direction. This is an important argument to reverse the decreasing trend in technology support policies, which OECD countries have been showing from the 2011-peak.

Our paper contributes to three streams of literature. First, we speak to the literature on the economics of climate change (Nordhaus, 2019) and consider the role of innovation in its mitigation. Notably, we focus on the effect of a largely neglected but economically relevant policy leverage, government sponsored R&D, on fostering the impact of clean innovation.

Second, we contribute to the literature on directed technical change and the environment (Acemoglu et al, 2012; Hemous and Olsen, 2021) in two respects. We focus on the impact that government sponsored R&D has on the development of new green technologies with a high impact on the development of subsequent innovations. In addition, we enlarge the scope of previous empirical applications and provide the first estimates of the effect that government sponsored R&D has on the generation of impactful clean technologies considering the whole spectrum of technologies related to climate change mitigation and adaptation; this allows us to go beyond energy-production technologies or the dominant focus on the transport industry.

Third, we contribute to an extensive literature in the economics of innovation, which has been looking at the innovation returns of public R&D through patent data (Howell, 2017; Plank & Doblinger, 2018; Azoulay et al., 2019; Santoleri et al., 2023). We add to this literature by posing an original focus on the effect of public R&D funding on innovation to face climate change and by proxying its impact through with patent citations.

2 Data and descriptive evidence

In the empirical analysis we assess whether new clean technologies resulting from R&D projects supported by government funding have a higher impact on subsequent technological development than those developed without public support. To do that, we rely on different sources of data.

From the 3PFL database (de Rassenfosse et al., 2019) we retrieve information on procurement contracts and research grants signed by the US government, and on the patents filed to protect the resulting inventions. The 3PFL database comprises information for 37,925 patents granted by the USPTO between 2005 and 2015.

We then complement the 3PFL database by retrieving, from the European Patent Office's worldwide statistical database (PATSTAT), all patents granted by the USPTO to the applicants contained in 3PFL during the same period. In other words, we add patents filed by the applicants in the 3PFL that are not linked to projects funded by the government. These patents are used to create the control group and to design a quasi-experimental estimation framework.

Finally, we gather further data on the patents included in our sample from the OECD Patent Quality Indicators Database (Squicciarini et al., 2013). We then compute a series of alternative patent citation measures to evaluate their impact on subsequent technological development, using the approach outlined by the OECD (2009). The final dataset includes 464,123 patents, pertaining to 4,086 different applicants, 36,966 of which are associated to a public contract.

Clean technologies are identified using the Y tagging of the Cooperative Patent Classification (CPC), and considering clean tech those patents classified with: i) code Y02, Technologies or applications for mitigation or adaptation against climate change, and/or; ii) code Y04, Information or communication technologies having an impact on other technology areas (of power generation and distribution).

In the final sample, clean-tech patents have been granted to 1,420 different applicants. The share of clean tech patents in the sample is about 8%, just slightly higher than the share of clean tech patents over the total patents granted at the USPTO during the same period (7%). Despite our sample includes only applicants that have received at least one government contract, it is nevertheless capable to mimic the overall share of clean technologies.

Table 1 reports summary statistics for the patents filed by applicants receiving at least one public contract in the 2005-2015 period. Patents in our sample receive on average 13.77 citations, belong to 3 applicants and have been developed by 3 inventors. The table further breaks down summary statistics by clean tech and non-clean tech patents. Clean tech patents receive on average more citations, are more original and have a higher number of inventors and applicants compared to non-clean tech ones.

Table 1: Summary statistics

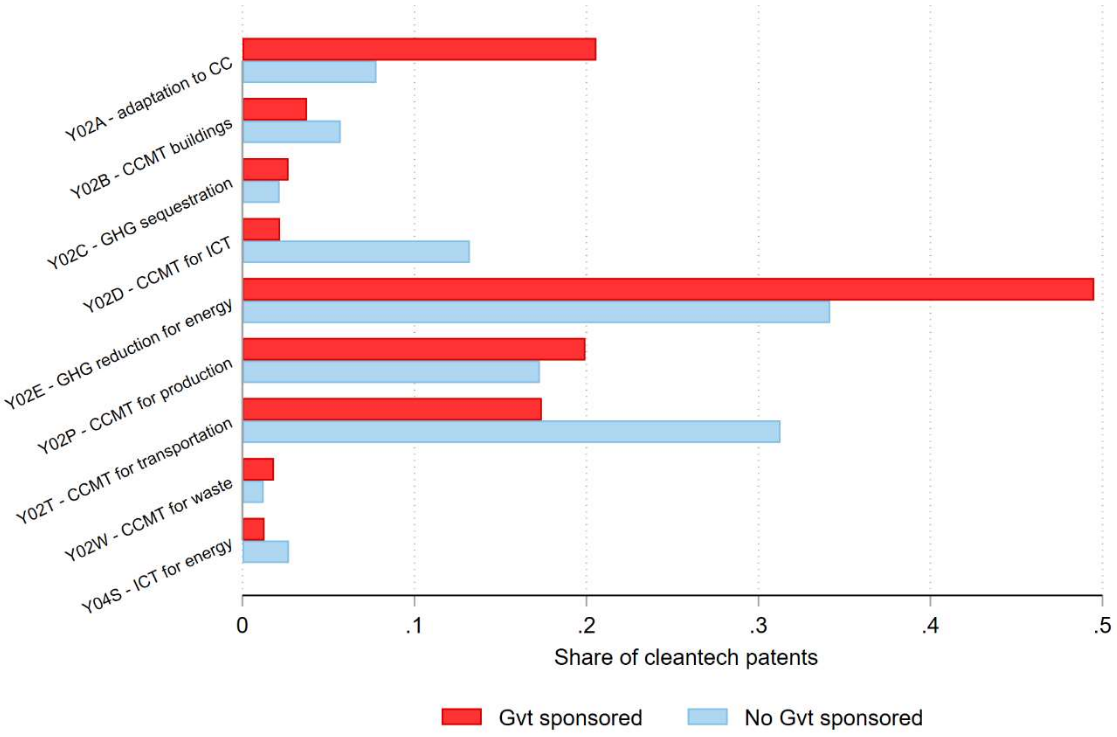
	mean	sd	min	max
All patents (n = 464,123)				
fwd_cits5	13.77	42.35	0	3054
Gvt R&D	0.0796	0.271	0	1
Originality	0.784	0.171	0	0.989
# of inventors	3.016	1.929	0	76
# of applicants	2.987	2.183	1	77
Non clean tech patents (n=425,394)				

fwd_cits5	13.46	41.34	0	3054
Gvt R&D	0.077	0.266	0	1
Originality	0.782	0.172	0	0.989
# of inventors	3.004	1.919	0	76
# of applicants	2.963	2.169	1	77
Clean tech patents (n=38,729)				
fwd_cits5	17.14	52.05	0	1892
Gvt R&D	0.114	0.318	0	1
Originality	0.814	0.154	0	0.988
# of inventors	3.144	2.035	0	61
# of applicants	3.254	2.314	1	62

Overall, nearly 8% of patents are developed within government funded projects; clean-tech patents are more likely to stem from government funding, 11.4% vs 7.7%. This suggests that the government concern for green technologies might have determined a non-random selection of funded projects, with a direct impact on the technologies developed by its contractors.

Figure 1 shows a substantial heterogeneity in the government support among clean technologies. The share of supported clean-tech patents is larger than the non-supported ones in the reduction of GHG emissions related to energy (Y02E) and in adaptation to climate change (Y02A). Conversely, non-sponsored patents weights more than sponsored ones in climate change mitigation in transportation (Y02T) and climate change mitigation in ICT (Y02D).

Figure 1 – Share of government sponsored and non-sponsored patents by type of clean technology.



Note: clean technologies are classified according to the 4-digit classes under the Y tagging of the CPC classification. Shares sum to more than 100% because patents can be associated to multiple CPC codes.

This descriptive evidence suggests that government support to clean technologies cannot be deemed as random, as it shows a clear tendency towards specific technologies, while others are developed more frequently through non-supported projects.

3 Estimation strategy and variables

We identify the effect of government support (treatment) on the development of impactful new (clean) technologies, by comparing the follow up citations of treated and non-treated patents in our sample. More precisely, we estimate a set of variants of the following equation:

$$citations_i = \beta GvtRD_i + X\gamma + \lambda_t + \delta_{tec} + \alpha_e + u_i \quad (1)$$

where the dependent variable is the number of citations received by patent i in a 5-years window. Following a long tradition in the literature, forward citations of a focal patent can be deemed a reliable proxy of its knowledge spillovers (Caballero and Jaffe, 1993; Jaffe and Trajtenberg, 1999; Hall et al., 2001), and of the importance that the relative new technology has for the development of subsequent ones. The higher the number of forward citations of the patent, the larger its knowledge spillovers, the greater the role of the relative knowledge for future waves of technologies (Dechezleprêtre et al., 2014; Guillard et al., 2021).

In equation (1) the parameter of interest is β, which captures the effect of government sponsored R&D ($GvtRD$) on the development of impactful clean technologies. X is a vector of variables which includes: the number of inventors reported in a patent document (team size), the number of entities participating in the development of the invention (# of applicants) and a measure of the originality of the invention protected by the patent (originality). This measure is computed as $1 - \sum_{j=1}^{n} s_j^2$, where s is the share of citations from patents that contain IPC codes (j) different from those reported in the cited patent document (Hall et al., 2001). λ_t refers to fixed effects for patent filing years and δ_{tec} to technology specific fixed effects. Technology and time fixed effects guarantee that the observed variance in citations between treated and non-treated patents will effectively capture differences in their impact not deriving from differences in the underlying technological opportunities or from changing citation patterns over time.

As we said, assuming that R&D government support can be deemed random is hardly sustainable, and the identification of the parameter β requires careful a consideration of possible sources of bias. The treatment is unlikely to be independent from the potential outcomes of government supported R&D projects for at least three reasons.

First, as shown in figure 1, the government tends to allocate more support to certain technologies over others, and the evaluation process may result in the selection of the most promising projects or companies for preferential treatment. Second, applicants might select those R&D projects characterized by higher uncertainty, and which are expected to take several years before being commercially exploitable, into the search for public support.

To account for these possible sources of selection bias, we include a number of control variables and technology fixed effects. The variables team size, # of applicants and originality are meant to capture project-specific characteristics that can lead to their selection into the treatment. The first two account for the relationship between collaboration in patenting and its research impact (Larivière et al., 2015). The originality variable instead accounts for the fact that riskier projects, relying on a diversified set of technical knowledge, can lead to more original and impactful inventions. Technology fixed effects are instead included to rebalance the estimation sample and level out the marked differences in the technological distributions of supported and non-supported patents (Figure 1). In an additional specification, we also adjust the regressions by including inverse probability weights from a selection into treatment equation, which includes all the variables used in equation (1).1

Second, government funded projects generate internal spillovers, which can increase the overall R&D potential of the receiving applicant, thus leading to the violation of the stable unit treatment value assumption (SUTVA). To account for this potential SUTVA violation, we include in the estimates the entity level fixed effects, α_e. This is a key element of our identification strategy. Its inclusion forces comparisons between treated and non-treated patents at the applicant level, thus controlling also for common unobservable determinants that may explain the residual variation in our dependent variable. Moreover, in section IV.B we recalculate our dependent variable excluding self-citations. In this way, we rule out the impact on subsequent technological development deriving from in-house R&D projects. As we will discuss more in detail later, the detailed

[1] In Appendix B, Table B1, we report results using differently computed weights and investigate the robustness of our findings to problems related to misspecification of the selection into treatment model, through augmented inverse-probability-weighted (AIPW) and inverse-probability-weighted regression adjustment estimators (IPWRA).

spillover analysis allows us also to provide evidence on the effect of government support from a societal perspective. Among the robustness checks we also assess whether our results might suffer from heterogeneity treatment bias.

A third source of bias may arise from sample selection. The sample contains only applicants that have received at least one public contract, which implies a selection per se: we do not observe the universe of US firms and research institutions. In other words, while we distinguish between treated and not-treated patents within a given applicant, we do not observe those patents developed by actors that have never received a public contract. However, it should be noted that the sample includes all applicants that have received a public contract in 10 years (the original 3PFL), implying that the selection is not specific to clean technologies; this makes possible selection issues less problematic in our case. Moreover, the selection may lead to an overestimation of the effect of government support only if the non-treated patents in the sample are consistently less impactful than patents developed by never-treated applicants. In other words, an overestimation of the effect of government support would require that the government systematically selects projects from applicants developing less impactful technologies. Currently, this seems to lack conclusive backing from both existing evidence and theoretical arguments. Further research can provide more insights and enhance our comprehension.

4 Results

4.1 Core estimations

The primary objective of this paper is to identify parameter β, which represents the effect of government R&D support on the development of impactful clean technologies. However, before discussing the main results we present estimations for the whole sample, including clean and non-clean technologies. The purpose of this analysis is to investigate whether government R&D support has a differentiated effect between the two in terms of subsequent technological development.

Table 2 reports the results of equation (1) using the full sample of patents, including a dummy for clean technologies and its interaction with *GvtRD*; citations are considered for a time span of 5 years. Results in column 1 do not include applicant fixed effects, which are instead included in column 2. With the inclusion of applicant fixed effects the coefficient attached to government sponsored R&D change sign, from positive to negative. Due to the heterogeneity of the estimation sample in terms of technologies and applicants, we do not think the results should be taken as overall evidence of the effect of government support. Instead, the results suggest that the government might tend to factor in the applicants' potential when evaluating projects: this confirms that intra-applicant comparisons are a key element to properly assess the effect of government R&D support on subsequent inventions.

Table 2 - Effect of government sponsored R&D on subsequent innovation – all technologies.

	# five-year forward citations	
	(1)	(2)
Gvt R&D	0.971**	-1.134**
	[0.262]	[0.336]
Clean tech	4.375**	4.287**
	[0.261]	[0.261]
Gvt R&D x clean tech	3.184*	2.278*
	[1.267]	[0.935]
originality	6.775**	5.189**
	[0.266]	[0.260]
team size	1.896**	1.804**
	[0.071]	[0.071]
# of applicants	0.010	-0.074
	[0.070]	[0.069]
Filing year FE	Yes	Yes
Technology FE	Yes	Yes
Applicant FE	No	Yes

F-test	71.030	40.983
R sq	0.047	0.117
N (Patents)	464,123	462,745

The unit of observation is patent application for the full sample. Dependent variable in all columns is the number of five-year forward citations. All estimates are OLS and include technology fixed effect at the 3-digit CPC level. Robust standard errors in parenthesis. + p<0.1, * p<0.05, ** p<0.01.

Table 2 confirms previous evidence showing that clean technologies have, on average, a higher impact on subsequent inventions compared to other technologies (Barbieri et al., 2020; Dechezleprêtre et al., 2017). The table also points to a higher citation premium for government sponsored clean technologies compared to non-government sponsored ones. Overall, these preliminary estimates reveal that clean technologies behave differently than non-clean ones, also when considering the role of public support.

We now focus on clean technologies and present the main results of the paper. Table 3 reports the estimates of equation (1) with respect to clean technologies, showing the absolute and relative effect of government R&D support on subsequent inventions. In column 1 we report the results of a linear specification without using inverse probability weighting scheme and applicant fixed effects. We then report results obtained by applying the inverse-probability weighting (column 2) and by adding applicant fixed effects (column 3). The comparison of the relative Average Treatment Effect (ATE) across columns, reported at the bottom of the table, allows us to evaluate the bias reduction deriving from the enrichment of the estimation approach.

Table 3 - Effect of government sponsored R&D on subsequent innovation – clean technologies.

	# five-year forward citations		
	(1)	(2)	(3)
Gvt R&D	6.472**	6.107**	4.427**
	[1.346]	[1.341]	[1.109]
originality	26.221**	32.572**	16.635**
	[1.409]	[2.322]	[1.819]
Team size	4.272**	5.103**	3.520**
	[0.384]	[0.639]	[0.420]
# of applicants	-0.951**	-1.420*	-0.864*
	[0.362]	[0.589]	[0.436]
Filing year FE	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes
Applicant FE	No	No	Yes
Weighting scheme	No	IPW	IPW

F test	29.197	20.829	16.011
Relative ATE	0.394**	0.360**	0.258**
	[0.084]	[0.082]	[0.066]
R sq	0.053	0.052	0.421
N (Patents)	38,729	36,726	36,245

The unit of observation is patent application for the sample of cleantech patents. Dependent variable in all columns is the number of five-year forward citations. Relative ATEs are computed as the relative difference between potential outcome means for treated and untreated groups ($\sum_i^{N_t} \hat{y}_i/N_t$-$\sum_i^{N_u} \hat{y}_i/N_u$)/ $\sum_i^{N_u} \hat{y}_i/N_u$ where $\hat{y}_i$ is the predicted value from the relevant regression model. Columns 2 and 3 are estimated using $\hat{p}(x_i)/(1-\hat{p}(x_i))$ to weight untreated observations and 1 otherwise. $\hat{p}(x_i)$ is the propensity score calculated as per Table B.2 in appendix B. Figures B.1 and B.2 in Appendix B report statistics relative to the propensity score procedure used to compute weights, showing a good performance in terms of bias reduction. All estimates are OLS and include technology fixed effect at the 4-digit CPC level. Robust standard errors in parenthesis. + p<0.1, * p<0.05, ** p<0.01.

The effect of government R&D support is high and significant in all the specifications. Interestingly, the bias reduction is particularly strong when including applicant fixed effects: the use of propensity score lowers the relative ATE (the ATE in terms of potential outcome) of public support by 5.7 percentage points, while when adding the fixed effects this reduces by an additional 10.7 percentage points.

According to our preferred specification (column 3), government supported clean technologies have about 26% more citations than non-supported ones within a 5-year window. In line with expectations, patents with a higher *originality* and a larger *team size* receive on average more citations, while somehow unexpectedly patents collaborated between more applicants show a lower number of citations. This last result may suggest that applicants tend to develop their more promising R&D projects (in terms of potential future impact) alone or in small collaborative settings.

4.2 Disentangling the spillovers of government sponsored R&D

In this section, we further disentangle the impact of government support in the development of impactful clean technologies by considering different types of knowledge spillovers.

First, we consider the knowledge spillovers generated by public R&D support outside the sphere of the focal applicant, by excluding those generated by its own citations. To clean our dependent variable from self-citations we use two different approaches: *i)* we eliminate a citation only if it is completely determined by the same applicant of the cited patent (*noself_nostric*); *ii)* we eliminate a citation if at least one applicant in the citing patent is also in the cited patent (*noself_strict*). In the former case, we rule out only sharp "intra-applicant" spillovers, but still allow for knowledge spillovers deriving from collaborations of the same applicant in subsequent projects (if a patent with applicants A and B cite a patent of applicant A, we still count the citation). In the second case, we capture pure knowledge spillovers, i.e. inter-applicant spillovers, because none of the citing applicants should be involved in the development of the cited patent. The results are reported in columns (1) and (2) of Table 4.

Second, we focus on the knowledge spillovers that flow from the applicants that have received government R&D support to the rest of the world. To do this, we exclude from our dependent variable all the citations from patents registered by applicants that have received at least one US public contract as recorded by the 3PFL. Like in the case of self-citations, we compute these spillovers using a non-strict and a strict definition; results are reported in columns (3) and (4).

Finally, we assess whether government R&D support helps generate clean technologies with higher international knowledge spillovers, thus having a higher impact on the subsequent technological development in other economies. To do so, we build two variables: *i)* cit_US, a binary variable taking value 1 is all citations of a given patent are generated only by US applicants (column 5); *ii)* geo_breadth, counting the number of applicant's countries of the citing patents (column 6).

The results reported in Table 4 suggest that spillovers effects are rather strong and not localized among the applicants receiving public support. In fact, the coefficient attached to government sponsored R&D is statistically significant at the usual level in columns 1 to 4. The magnitude of the coefficient decreases when using the stricter definition of spillovers, which is consistent with the reduced number of citations considered. However, the relative average treatment effects do not vary substantially from the main estimations (see Table 3, column 3), confirming the sizeable effect of government support on follow up inventions.

Table 4 - Effect of government sponsored R&D on different kinds of knowledge spillovers, clean technologies

	(1)	(2)	(3)	(4)	(5)	(6)
	noself nostrict	noself strict	out nostrict	out strict	cit US	geo breadth
Gvt R&D	4.376**	3.151**	4.350**	2.176**	0.006	0.137+
	[1.017]	[0.866]	[1.051]	[0.672]	[0.007]	[0.073]
originality	15.795**	12.856**	16.104**	9.132**	0.171**	1.453**
	[1.764]	[1.655]	[1.800]	[1.241]	[0.018]	[0.119]
Team size	3.049**	2.773**	3.259**	2.110**	0.010**	0.238**
	[0.370]	[0.360]	[0.389]	[0.262]	[0.002]	[0.019]
# of applicants	-0.692+	-0.824*	-0.783+	-0.562*	-0.003*	-0.051**
	[0.380]	[0.372]	[0.401]	[0.268]	[0.002]	[0.019]
Filing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Applicant FE	Yes	Yes	Yes	Yes	Yes	Yes
Weighting scheme	IPW	IPW	IPW	IPW	IPW	IPW
Relative ATE	0.286**	0.256**	0.274**	0.230**	0.007**	0.041+
	[0.067]	[0.071]	[0.067]	[0.072]	[0.009]	[0.022]
N (Patents)	36,245	36,245	36,245	36,245	36,245	36,245

The unit of observation is patent application for the sample of cleantech patents. Relative ATEs are computed as relative difference between potential outcome means for treated and untreated groups ($\sum_i^{N_t} \hat{y}_i/N_t$-$\sum_i^{N_u} \hat{y}_i/N_u$)/ $\sum_i^{N_u} \hat{y}_i/N_u$ where $\hat{y}_i$ is the predicted value from the relevant regression model. All columns are estimated using $\hat{p}(x_i)/(1-\hat{p}(x_i))$to weight untreated observations and 1 otherwise. $\hat{p}(x_i)$ is the propensity score calculated as per Table B2 in Appendix B. For the regression adjustment via propensity score, we enforce a common support by removing the 5% of the treatment observations at which the propensity score density of the control observations is at a minimum. All estimates are OLS and include technology fixed effect at the 4-digit CPC level. Robust standard errors in parenthesis. + p<0.1, * p<0.05, ** p<0.01.

Results reported in columns 5 and 6 show that the spillovers generated by government supported clean patents are not more localized within the US than privately funded ones but have a higher geographical breadth: the technology is further developed by applicants from a larger basket of countries. This suggests that spillovers from government supported clean technologies may differ from those in other areas of intervention. Moreover, in line with models of growth emphasizing the strategic complementarities in clean research across countries (Aghion et al., 2015; Dechezlepretre et al., 2017), the larger geographical scope of citations is consistent with the idea that policies supporting the development of clean technologies can have an effect in fostering the global generation of such technologies.

4.3 Robustness tests

In this section we present a battery of robustness checks to further corroborate our main results.

First, while in our analysis we control for different types of spillovers and for observable differences in potential outcomes, with the data at stake we are not able to allocate budget at the patent level. The budget of government supported projects is not homogeneous and can be allocated to different activities other than R&D for technological development; moreover, there are cases of multiple patents linked to the same government supported project. This mean that the treatment might be not homogeneous, and we cannot directly model it. To assess whether the heterogeneity in the government R&D support can be an issue when trying to identify its effect on follow up citations, we run two ancillary regressions at the applicant level. In the first, we assess whether higher amounts of government support induce more clean tech patents. In the second, we assess whether higher amounts of government support lead to more citations to the overall portfolio of supported patents once controlling for their number. If the coefficient attached to government support is statistically significant in the former but not in the latter, this would be indirect evidence that the heterogeneity in the treatment is not a major issue when assessing its effect on the impact of supported clean tech on follow up innovations.

The results reported in Table 5 suggest that this is the case. Higher amounts of government R&D support lead to a higher number of clean tech patents, but once controlling for clean tech patents it has not effect on the number of citations received.

Table 5: The effect of government sponsored R&D on the quantity and quality of inventions - cleantech sample

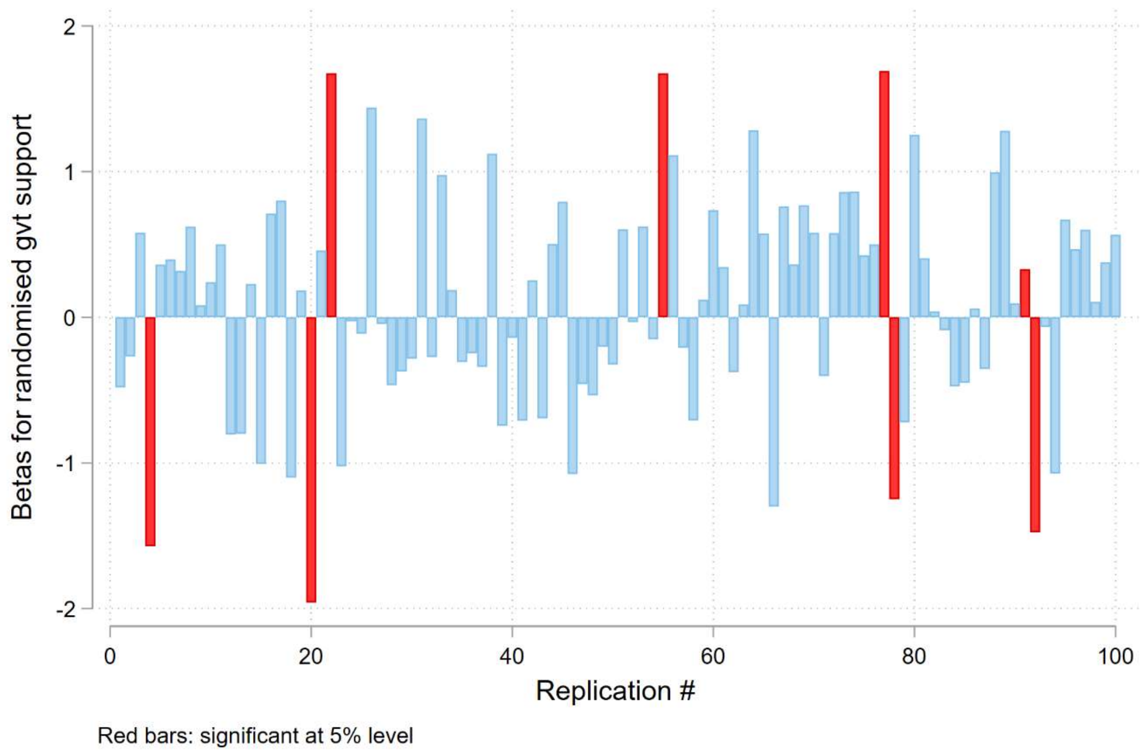
	(1) # green Gvt patents	(2) # citations to green patents
Amount of Gvt R&D	0.082**	-1.497
	[0.028]	[0.996]
# green Gvt patents		31.500**
		[11.378]
Avg. team size	0.128	37.426**
	[0.123]	[11.398]
Avg. # of applicants	0.098	-0.014
	[0.089]	[10.099]
Avg. originality	-0.165	170.284
	[1.185]	[88.706]

Constant	2.483*	-260.113*
	[1.197]	[103.976]
R sq	0.320	0.328
N (applicants)	868	868

Regressions are based on the 868 applicants that received government sponsored R&D and developed green technologies. The dependent variable in column 1 is the number of green patents sponsored by public R&D and in column 2 the number of citations received by green government R&D sponsored patents. Gvt R&D amount is the total amount received by the applicant. Estimates in both columns include controls for the average number of inventors, average number of applicants, the average originality index and the share of patents in different cleantech technological classes. Column 2 includes also the number of number of green patents sponsored by public R&D. + p<0.1, * p<0.05, ** p<0.01

Second, we run a randomised falsification test by randomly assigning treatment across our sample of clean tech patents while keeping the share of treated patents constant. We build 100 different replications of our favourite specification (Column 3 of Table 3) to assess whether a placebo government support would still exert a positive effect on forward citations. Figure 2 displays the coefficients attached to the placebo government R&D support for the 100 replications: the figure shows that we cannot reject the hypothesis that the coefficient is equal to zero, providing further evidence supporting our results.

Figure 2: Randomised falsification test



In the figure are reported the coefficients attached to GVT R&D (equation 1) when treatment is randomly distributed across clean patents. As in our preferred specification (Table 3, column 3), the estimations include applicant fixed effects and probability weights.

Third, we re-run our favourite specification by weighting observations by the inverse of the size of applicants' clean tech patent portfolios. In our sample, the number of applicants' observations is proportional to the number of their clean tech patents; giving the same weight to each applicant, this reweighting scheme ensures that results are not driven by applicants with larger portfolios. The results, reported in Table 6 column 1, confirm the positive effect of government support.

Table 2: Effect of green government sponsored R&D on subsequent innovation – robustness checks

	# five-year forward citations		# seven-year forward citations	# five-year forward citations		
	(1)	(2)	(3)	(4)	(5)	(6)
Gvt sponsored R&D	6.593*	6.257**	6.411**	0.233**	3.733**	5.467*
	[2.872]	[1.232]	[1.441]	[0.048]	[1.091]	[2.436]
originality index	32.189**	9.774**	20.327**	1.435**	16.433**	18.574**
	[3.647]	[1.287]	[2.112]	[0.134]	[1.805]	[4.651]
Team size	6.222**	1.961**	4.491**	0.127**	3.446**	1.671**
	[1.071]	[0.254]	[0.471]	[0.009]	[0.411]	[0.349]
# of applicants	0.056	-0.296	-1.078*	-0.014	-0.900*	0.236
	[1.193]	[0.271]	[0.478]	[0.010]	[0.424]	[0.316]
Filing year FE	Yes	Yes	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
Applicant FE	No	Yes	Yes	Yes	Yes	Yes
Filing year X Tech FE	No	No	No	No	Yes	No
Model	OLS	OLS	OLS	Poisson	OLS	OLS
Weighting scheme	GPAT	IPW	IPW	IPW	IPW	IPW
SEs	Robust	Robust	Robust	Robust	Robust	CPC-Year
F test	5.826	15.888	17.994	.	52.906	5.103
Rel ATE	0.358*	0.445**	0.284**	0.262**	0.216**	0.345*
Rel ATE SE	[0.160]	[0.090]	[0.065]	[0.060]	[0.065]	[0.155]
R sq	0.085	0.287	0.423	.	0.425	0.424
N (Patents)	36,245	25,025	36,245	36,238	36,244	31,058

The unit of observation is patent application for the sample of cleantech patents. Dependent variables are the number of five-year forward citations in columns 1, 2, 4, 5 and 6 and the number of seven-year forward citations in column 3. Relative ATEs are computed as relative difference between potential outcome means for treated and untreated groups ($\sum_i^{N_t} \hat{y}_i/N_t$-$\sum_i^{N_u} \hat{y}_i/N_u$)/ $\sum_i^{N_u} \hat{y}_i/N_u$ where $\hat{y}_i$ is the predicted value from the relevant regression model. Column 1 regression is weighted by the inverse of the number of cleatech patents in the applicant portfolio. Columns 2 and 3 are estimated using $\hat{p}(x_i)/(1-\hat{p}(x_i))$to weight untreated observations and 1 otherwise. $\hat{p}(x_i)$ is the propensity score calculated as per Table B2 in Appendix B. For the regression adjustment via propensity score, we enforce a common support by removing the 5% of the treatment observations at which the propensity score density of the control observations is at a minimum. All estimates are OLS and include technology fixed effect at the 4-digit CPC level. Robust standard errors in parenthesis. + p<0.1, * p<0.05, ** p<0.01.

Fourth, we test the robustness of our results against a more conservative definition of clean technologies. We build upon Dechezleprêtre et al. (2021) and define clean patents using 4-digit CPC technological classes Y02B, Y02C, Y02E and Y02T.[2] Results from the estimation on this sub-set of clean technologies, reported in Table 6 column 2, still confirm our main results and possibly magnifies the effect of government support in terms of relative ATE. Column 3 in Table 6 further shows the results when using a 7-years window in the computation of the number of forward citations. While the coefficient attached to government support is higher than that for the 5-years window, the effect of government support in terms of relative ATE is in line with our main results.

Column 4 in Table 6 presents the results for a (pseudo-)Poisson regression model with multiple high-dimensional fixed effects (Correia, 2020), ensuring the robustness of our findings to the count data format of our dependent variable (number of citations). Column 5 incorporates fixed effects for each combination of patent filing year and technological class (CPC at the subclass level, e.g. Y02A). Finally, Column 6 reports results with standard errors clustered at the same level (patent filing year-technological class level).[3] Reassuringly, all robustness checks produce outcomes consistent with our baseline results.

4.4 The distributional effects of government sponsored R&D

In this section, we assess the distributional effects of R&D government support on follow up innovations. To do so, we implement the recentered influence function (RIF) of the unconditional quantile (Firpo et al., 2009), to evaluate the impact of changes in the non-treated to treated (government supported) status on quantiles of the marginal distribution of forward citations.

Previous results could be eventually interpreted as follows: the government is able to systematically define/select technological needs/solutions with a potential higher impact on follow up innovations, compared to other actors in the economy. Despite lock-in effects and the possible local search performed by private actors, this is a rather strong result to be put forward. One can instead expect that in most cases the government support will not have a real effect. Conversely, it can be expected to incentivise research in research areas with lower expected private returns in the short term and thus increase the probability that some key technologies are developed. In other words, the (average) impact of government R&D support discussed above may be driven by the highly cited patents in the sample.

Therefore, the relevance of assessing the distributional aspects of the effect found in the previous sections derives from the assumptions underlying average effects and the interpretation of the relative results. Figure 3 shows the distribution of citations to clean tech patents comparing the group of patents resulting from

[2] These four CPC codes groups technologies related to buildings, to GHG capture and storage, to reduction of GHG in energy production and distribution, and to transportation. In other words, from our definition of clean tech we drop patents with codes: Y02A, Y02D, Y02P, Y02W and Y04S (see figure 1 for short labels).

[3] Recent discussions in the econometrics literature suggest that clustered standard errors may be overly conservative, and the appropriate level of clustering should be carefully chosen (Abadie et al., 2023). In our study, it is not advisable to cluster standard errors at the applicant level, due to the high number of clusters (1,400), many of which have few observations. Consequently, we have decided to cluster standard errors at the technology-year level, aligning with the evidence of a non-random distribution of government support at the technology level (see Figure 1) and potential yearly differences, resulting in 144 clusters. However, we had to exclude 5,187 patents because they were assigned to more than one 4-digit CPC code. For this reason, we do not apply clustered standard errors in all specifications.

projects supported by the government with that not originated by government supported R&D projects. The figure shows that the distribution of patents citations is rather skewed and suggests that differences between government supported and not supported patents are not constant along the distribution. At the bottom of the citation distribution supported and not supported patents do not differ much, with the latter showing a slightly higher fraction of patents. Instead, government sponsored cleantech patents are more frequent in the upper tail of the citation distribution, suggesting that the effect of government support operates through the development of most impactful clean technologies.

Figure 3: Fraction of cleantech patents for government sponsored and non-sponsored patents, by number of citations.

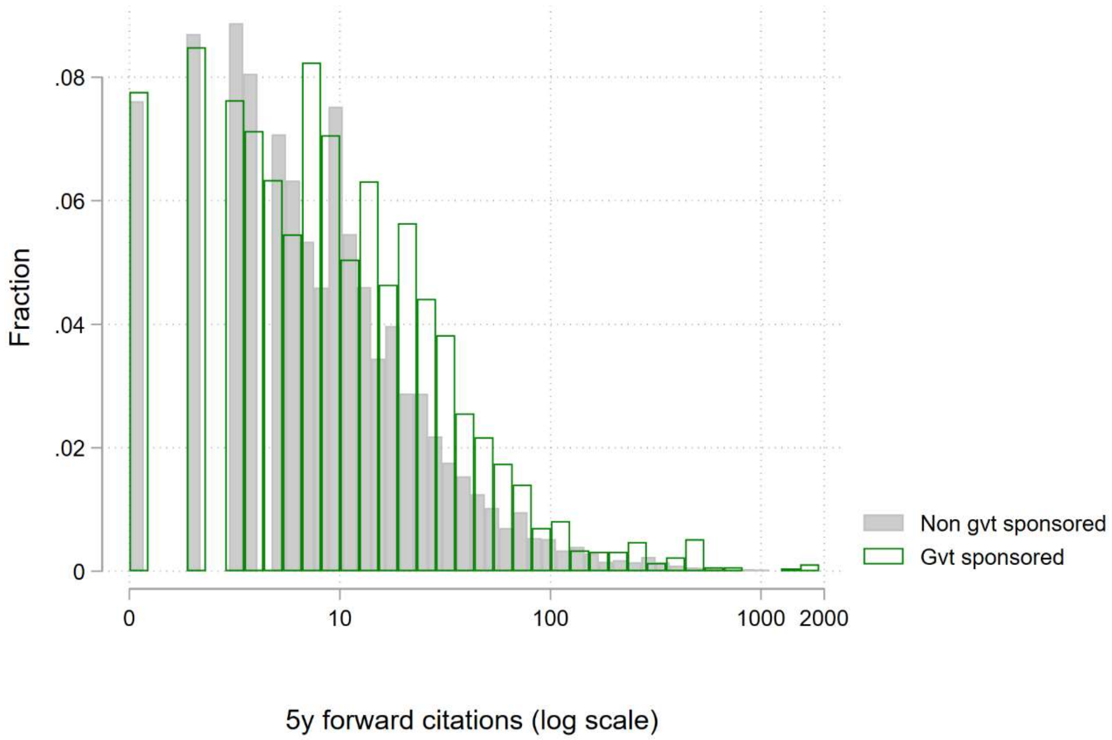


Table 7 reports the results of the RIF estimations on the quantiles of the citations distributions. Consistently with the argument and the descriptive evidence above, the effect of the government R&D support is visible only among the third and fourth quintile of the citations' distribution, where it is quantifiable in about 8.1% and 8.6% citations with respect to the respective potential outcome. Interestingly, also the coefficients attached to *originality* sizably increases along the quintile of the distributions, confirming the general result that more original (and more risky) clean patents may have a higher impact on follow up innovation.

Table 3: Effect of government sponsored R&D on subsequent innovation, distributional effects via RIF regressions for clean tech

	(1)	(2)	(3)	(4)
	20th quantile	40th quantile	60th quantile	80th quantile

Gvt R&D	0.160	0.264	0.722*	1.610*
	[0.101]	[0.177]	[0.343]	[0.821]
originality	1.827**	3.120**	5.982**	15.097**
	[0.220]	[0.311]	[0.538]	[1.320]
Team size	0.122**	0.231**	0.521**	1.777**
	[0.019]	[0.030]	[0.059]	[0.176]
# of applicants	0.018	0.004	-0.003	-0.325+
	[0.020]	[0.031]	[0.059]	[0.171]
Filing year FE	Yes	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes	Yes
Applicant FE	Yes	Yes	Yes	Yes
Weighting scheme	IPW	IPW	IPW	IPW
Relative ATE	0.069	0.054	0.081**	0.087+
	[0.044]	[0.037]	[0.039]	[0.045]
N (Patents)	36,726	36,726	36,726	36,726

The unit of observation is patent application for the sample of cleantech patents. Dependent variables are the number of five-year forward citations. Relative ATEs are computed as relative difference between potential outcome means for treated and untreated groups ($\sum_i^{N_t}\hat{y}_i/N_t$-$\sum_i^{N_u}\hat{y}_i/N_u$)/ $\sum_i^{N_u}\hat{y}_i/N_u$ where $\hat{y}_i$ is the predicted value from the relevant regression model. All columns are estimated using $\frac{\hat{p}(x_i)}{1-\hat{p}(x_i)}$ to weight untreated observations and 1 otherwise. $\hat{p}(x_i)$ is the propensity score calculated as per Table B2 in Appendix B. For the regression adjustment via propensity score, we enforce a common support by removing the 5% of the treatment observations at which the propensity score density of the control observations is at a minimum. All estimates include technology fixed effect at the 4-digit CPC level. Robust standard errors in parenthesis. + p<0.1, * p<0.05, ** p<0.01.

Finally, we further explore the distributional effect of government R&D support by running an ordered logit regression. By doing so, we do not take citations at their face value but rather sort patents according to their relative ranking, considering deciles of the citation distribution. This approach has the advantage of providing a framework not influenced by the fact that a good number of patents have no or few citations and that the variability in the patent citations at the bottom of the distribution is very small. Results, reported in figures B.5 and B.6 are in line with the RIF regressions, the effect of government R&D support is statistically different from zero after the 5th decile. While the effect of government support remains strong and positive on average, it operates mainly by favouring the development of the most impactful clean technologies.

5 Concluding remarks

Modern endogenous growth models applied to the environment have shown that science-push policies play an important role for the development of clean technologies (Acemoglu et al., 2012; 2016; Hémous and Olsen, 2021). Facing the path-dependent nature of technical change, public support can help firms internalize the (high) long term social returns of clean technologies and break the cumulative advantages of dirty ones.

In this work, we uncover the role of government R&D support in affecting the pace and direction of clean technological change, thus pointing to a crucial policy leverage for the green transition. Considering the importance of radically new research projects, which yield high impact innovative outcomes and retaining the firms' obstacles to invest in them (Azoulay et al., 2019; Mukherjee and Pennings, 2004; Scotchmer, 1991), we have argued that a largely neglected but fundamental role of public R&D is inducing the development of clean technologies with high knowledge spillovers on subsequent ones.

By building up a new dataset, comprising all USPTO patents granted between 2005 and 2015 to applicants that received procurement contracts or research grants from the US government, we have obtained robust evidence on the positive effect of US government R&D support through a quasi-experimental estimation framework. Technology-push policies can direct research efforts toward (specific) clean technologies and favour the development of technologies with a high impact on the subsequent generation of knowledge.

The impact of the US government R&D support on high impactful clean technologies has been remarkable in size. Using forward citations from follow up patents as a proxy of knowledge spillovers, government supported clean technologies show about 26% more citations (in the following 5-years) than non-supported ones. By distinguishing intra- from inter-entities spillovers, we show that R&D government support facilitates clean innovations whose subsequent technological impact is also greater in social terms. R&D government support does not affect the domestic-foreign patterns of spillovers, but it widens their geographical distribution. Finally, the effect of R&D government support is notable in facilitating clean technologies that have the most fundamental basic role in supporting the unfolding of a new green technological paradigm.

Our results have important implications both for the modelling of climate change policies and for their undertaking. In the former respect, theoretical conclusions about the direction of technical change towards sustainable growth should be based on more sophisticated hypotheses about the spillovers of clean and risky technologies and about their implications for R&D investments and learning. In the second respect, under the increasing pressure of climate change, our analysis provides a strong case to revert the overall decreasing trend in technology support policies and to reconsider their key-role within the packages of governments' green policy interventions.

Our results do also contribute to the advancement of academic literature along three different but interrelated research streams. First, we contribute to an enrichment of the literature on the economics of climate change, which highlights the importance of technology-push policies in mitigating its impacts. Second, providing empirical evidence on its relevance for the development of (the most) impactful clean technologies we enrich the literature on directed technical change and the environment with a new focus on the effect of government sponsored R&D on technological development. Finally, we add to the literature about the innovation returns of public R&D through patent data, by extending its assessment to clean patent data and to different types of knowledge spillovers.

In doing so, we provide an original empirical link between the so-called "Nelson-Arrow paradigm" (Traijtenberg, 2012) in innovation policy that has been looking at the innovation returns of public R&D and the recent debate about public R&D in front of social challenges, of which environmental sustainability is for sure one of the most pressing (Foray et al., 2012).

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Annexes

A Data Construction

From the 3PFL database (de Rassenfosse et al., 2019) we retrieve information on procurement contracts and research grants signed by the US government, and on the patents filed to protect the resulting inventions. The 3PFL database comprises information for 37,925 patents granted by the USPTO between 2005 and 2015.

In order to create the control group of non-treated patents we proceeded as follows:

i) The 3PFL does not provide a code that can be directly used in Patstat to identify the patent applicants. Therefore, we have used the patent_nr field (the number that identifies the publication of the granted application at the USPTO) from the 3PFL database to retrieve all the person identifiers associated to 3PFL patents from Patstat. This reduces the sample of patents to 37,003 as we excluded patents where the inventor was also the applicant, and no other applicant was reported in PATSTAT.

Table A.1 shows, for each 3PFL patent the number of applicants in Patstat and the number of contractors in 3PFL. In most cases the correspondence was 1:1 and the applicant-contractor pair directly identified.

Table A.1: Correspondence between number of contractors in 3PFL and number of applicants in Patstat for clean tech patents.

		Number of contractors in 3PFL								
		1	2	3	4	5	6	7	8	9
Number of applicants in PATSTAT	1	30,213	3,002	332	40	13	2	1		1
	2	2,309	483	93	24	1		1		
	3	303	70	28	2	1				
	4	55	13	2	1					
	5	10	3							
	6									
	7	1								

Note: the selection excluded patents where the inventor was also the applicant and no other applicant was reported.

ii) In all the cases where the matching did not result in a 1:1 or 1:many correspondence we have disambiguated the matching using the names of applicants and contractors in the two databases.

In all the cases where the number of applicants and contractors was the same (first row and first column of Table A.1) we associated the relative entries using the Levenshtein distance, which provided a measure of similarity between the names reported in the two databases. All other cases have been manually disambiguated. As a result, we created a correspondence table between applicant codes (*person_id*) in Patstat and the contractor identifier reported in 3PFL.

iii) We used the disambiguated list of *person_id* to retrieve all the patents granted to the same applicant over the 2005-2015 period. These patents represent the control group.

B. Robustness Checks and Specifications

Misspecification of outcome and treatment models: doubly robust estimators

To assess the robustness of our findings to possible issues related to misspecification of the selection into treatment model we rely on the augmented inverse-probability-weighted (AIPW) and the inverse-probability-weighted regression-adjustment (IPWRA) estimators.

While the IPW estimator used in the main analysis models only the treatment probability, the AIPW estimator model both the outcome and the treatment probability. The advantage of the AIPW is that it is enough that only one of the two models is correctly specified to consistently estimate the treatment effect; for this reason, this type of estimator is known as a property known as being. The AIPW estimator includes an augmentation term that corrects the estimator when the treatment model is incorrect. This augmentation term vanishes when the treatment is properly specified, and the sample size is large.

Similarly, inverse-probability-weighted regression-adjustment (IPWRA) estimators integrate models for the outcome and treatment status and possess the double robustness property. IPWRA estimators utilize the inverse of the estimated treatment-probability weights to estimate regression coefficients that correct for missing data. These coefficients are then used to calculate potential outcome means (Wooldridge, 2010).

To the best of our knowledge, there is no literature that compares the relative efficiency of AIPW and IPWRA estimators, so we report results from both approaches in the table below. Results show high and significant coefficients. As expected, coefficients are higher than in our favorite specification (Column 3 in Table 3 in the main text) as AIPW and IPWRA estimators do not allow to control for the applicant fixed effects.

Table B.1: Effect of green government sponsored R&D on subsequent clean innovation – doubly robust estimators (AIPW and IPWRA)

	(1)	(2)
Gvt R&D	9.074**	9.250**
	[1.801]	[1.761]
Controls	Yes	Yes
Filing year FE	Yes	Yes
Technology FE	Yes	Yes
Applicant FE	No	No
Estimator	AIPW	IPWRA
Relative ATE	0.566**	0.577**
	[0.114]	[0.111]
N (Patents)	36,726	36,726

+ p<0.1, * p<0.05, ** p<0.01

Results from the IPW treatment model and alternative weights

Table B.2: Selection into green government sponsored R&D – propensity score.

	(1)
originality	0.458**
	[0.065]
Team size	0.015**
	[0.006]
# of applicants	0.014*
	[0.006]
CC adaptation (Y02A)	0.591**
	[0.033]
CCMT buildings (Y02B)	-0.158**
	[0.047]
GHG capture (Y02C)	0.040
	[0.057]
CCMT ICT (Y02D)	-0.763**
	[0.051]
GHG energy (Y02E)	0.297**
	[0.027]
CCMT production (Y02P)	-0.007
	[0.027]
CCMT transport (Y02T)	-0.281**
	[0.030]
CCMT waste (Y02W)	0.135+
	[0.072]
ICT for energy (Y04S)	-0.320**
	[0.069]
Filing year FE	Yes

Technology FE	Yes
Chi2 test	1643.711
McFadden's R sq	0.070
N (Patents)	38657

+ p<0.1, * p<0.05, ** p<0.01

Figure B.1: Variance ratio of residuals vs bias before and after matching

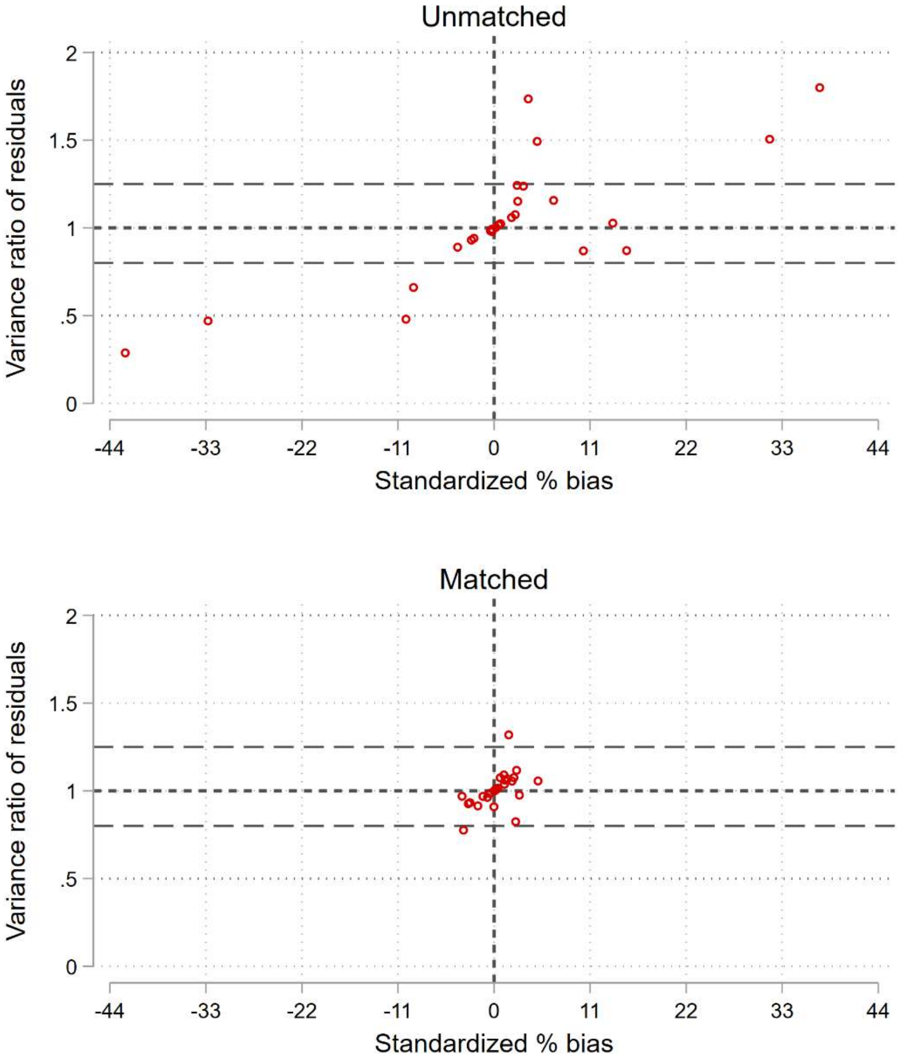
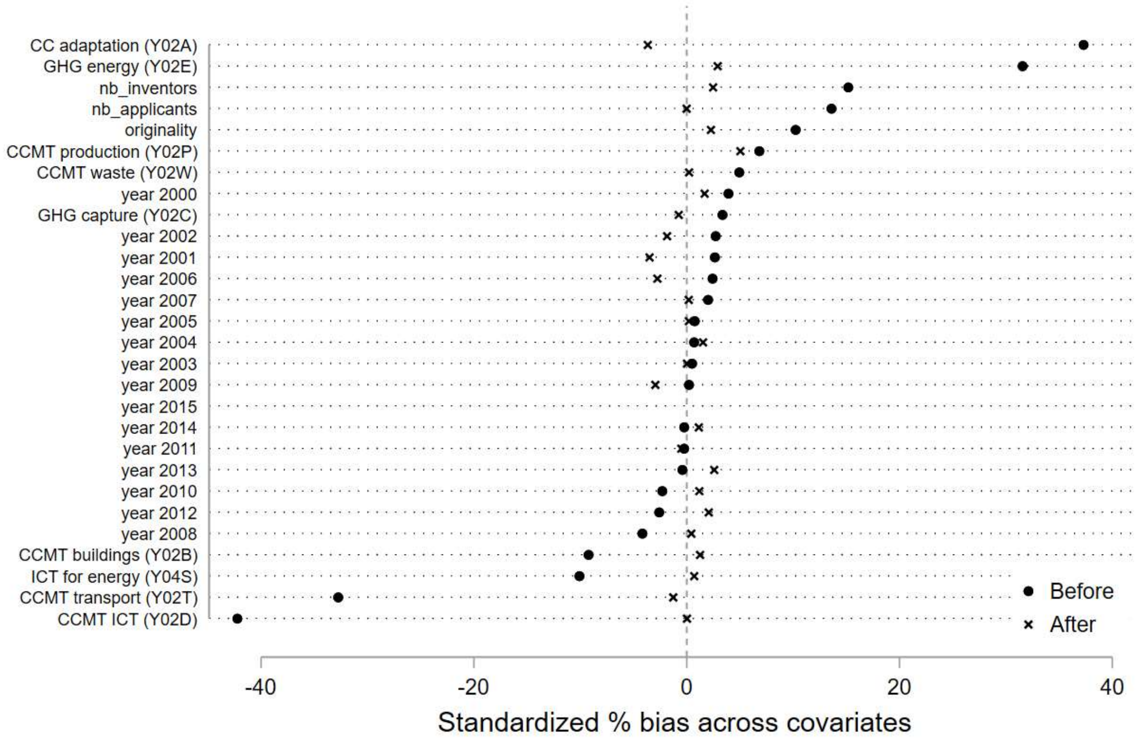


Figure B.2: Covariate bias before and after matching



We test the robustness of our results to alternative weights used for regression adjustment. First, we implement two differently defined weights coming from the propensity score calculation. The first weight rebalances the treated group only: it takes value $(1-\widehat{p_\iota})/\hat{p}$ for the patents having received government R&D support and 1 otherwise (with $\widehat{p_\iota}$being the fitted value from Table B2 above. The second weight is a standard inverse probability weight taking value $1/\hat{p}$ for cleantech patents receiving government R&D support and $1/(1-\hat{p})$ otherwise. Following existing work (Hirano el al., 2003; Brunell and Di Nardo, 2004), both weights are computed preserving proportions between the treated and untreated group. Finally, we compute weights from a coarsened matching procedure (Iacus et al., 2012). Figures B.3 reports comparison between treated and untreated patents in relation to global and local imbalance measures. The global imbalance statistic is calculated as the local imbalance measures difference between the multidimensional histogram of pretreatment covariates in the treated group and the same in the control group. In our specific case, the value of 0.672 is the reference point for the unmatched data, and a decrease in the value after matching (0.597) indicates a reduction in the level of imbalance. Similar reductions in the local imbalance measures are found for the individual variables. Figure B.4 provides a comparison of variable means before and after matching and shows an important reduction in bias following the matching procedure. Overall, the two figures reassure us about the ability of the chosen approach to reduce bias from observables.

Figure B.3: Multivariate and local imbalance measures with and without government R&D support.

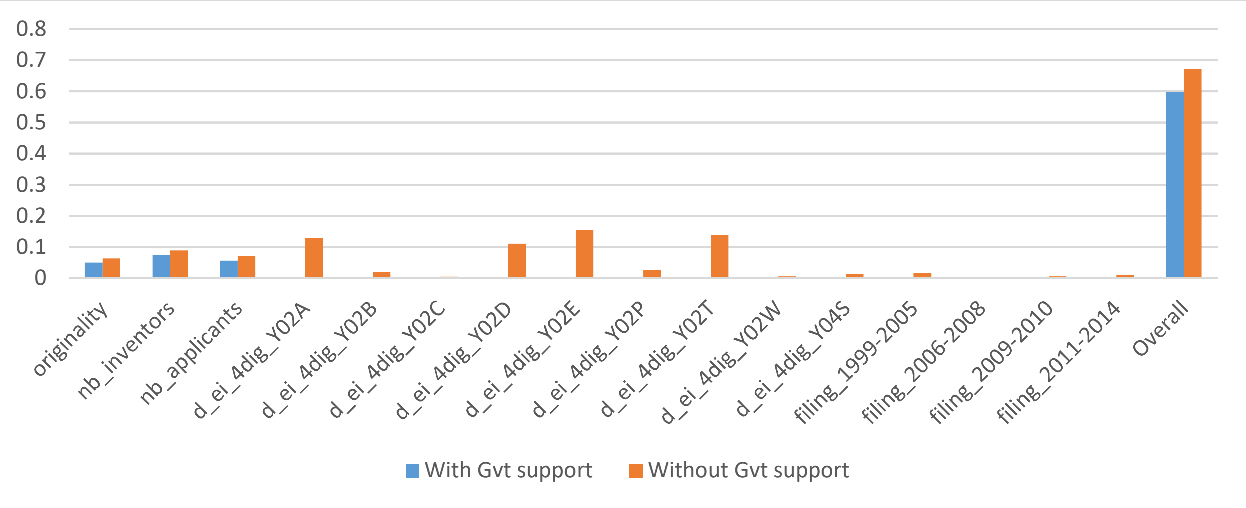


Figure B.4: Comparison of variable means with and without Government R&D support**.**

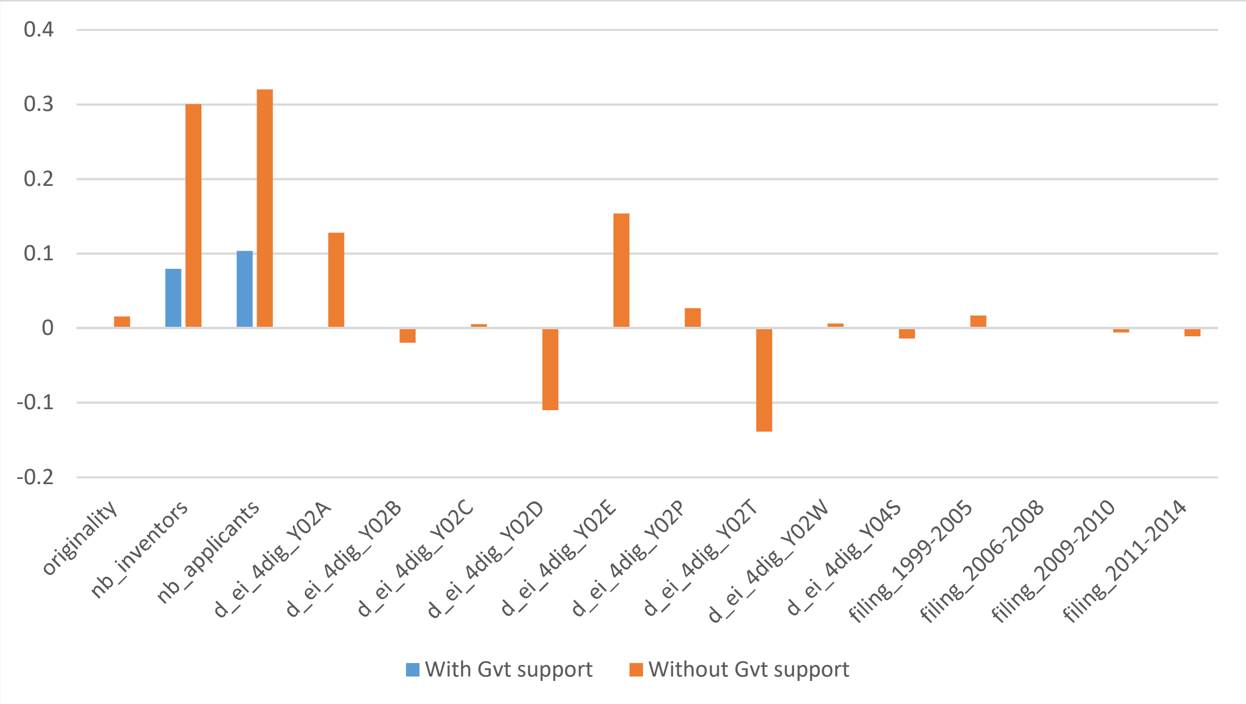


Table B.3 shows results using the set of three weights described above. We notice that implementing the CEM weight reduces the sample to 32,132 observations due to the need to prune observations that have no closed matches on covariates in both treated and control groups. Coefficients on the effect of Gvt R&D for the models using alternative definitions of propensity score weights show higher coefficients compared to our baseline estimates (see column 3 in Table 3 in the text), while the CEM weighted regression has a coefficient very much in line with the one reported in our favorite specification (3.78 vs 4.43).

Table B.3: Effect of green government sponsored R&D on subsequent innovation – alternative weights for regression adjustment

	(1)	(2)	(3)
Gvt R&D	5.174**	5.159**	3.784**
	[1.226]	[1.201]	[1.014]
originality	15.557**	15.786**	17.724**
	[1.244]	[1.310]	[1.997]
Team size	3.038**	3.095**	1.931**
	[0.311]	[0.319]	[0.353]
# of applicants	-0.577+	-0.608+	-0.032
	[0.311]	[0.321]	[0.335]
Filing year FE	Yes	Yes	Yes
Technology FE	Yes	Yes	Yes
Applicant FE	Yes	Yes	Yes
Weighting scheme	IPW	IPW	CEM
F test	19.971	19.823	8.617
Relative ATE	0.316**	0.313**	0.223**
Relative ATE SE	[0.076]	[0.074]	[0.062]
R sq	0.416	0.411	0.434
N (Patents)	36245	36245	31644

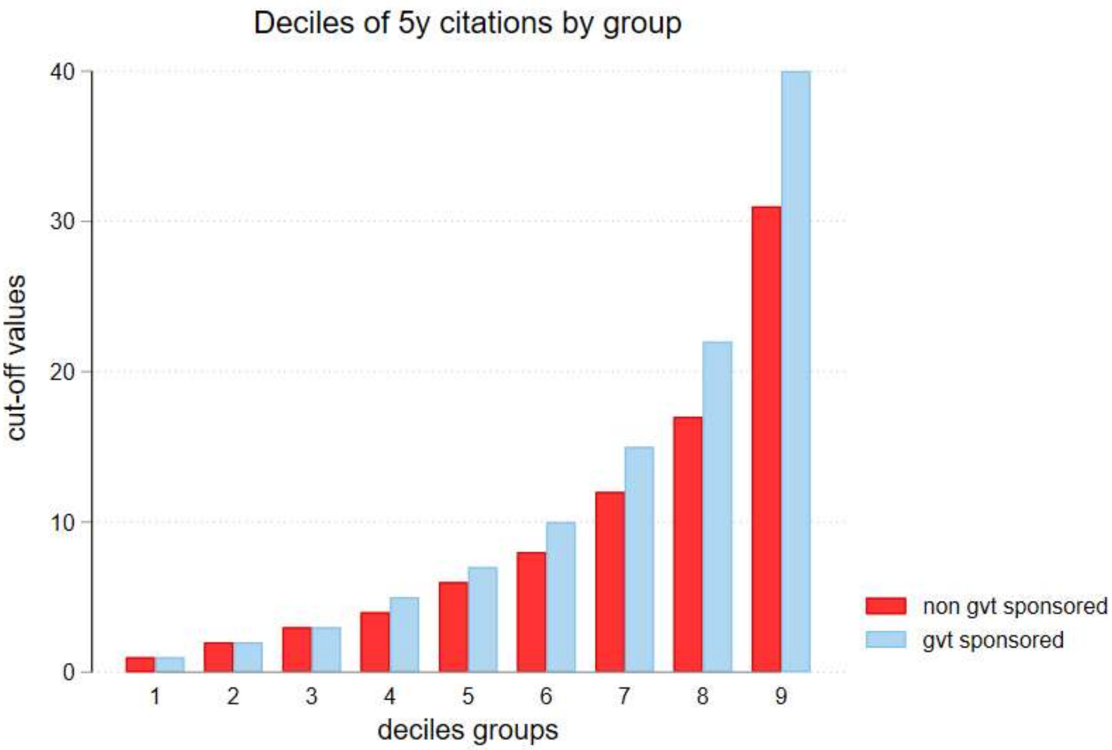
+ p<0.1, * p<0.05, ** p<0.01 For the regression adjustment via propensity score, we enforce a common support by removing the 5% of the treatment observations at which the propensity score density of the control observations is at a minimum.

Alternative distributional effects of government sponsored clean technologies

Figure B.5 displays the cut-off of the deciles of 5-years citations for supported and not supported patents: both the cut-offs and the differences between supported and not supported patents increase more than linearly along the distribution.

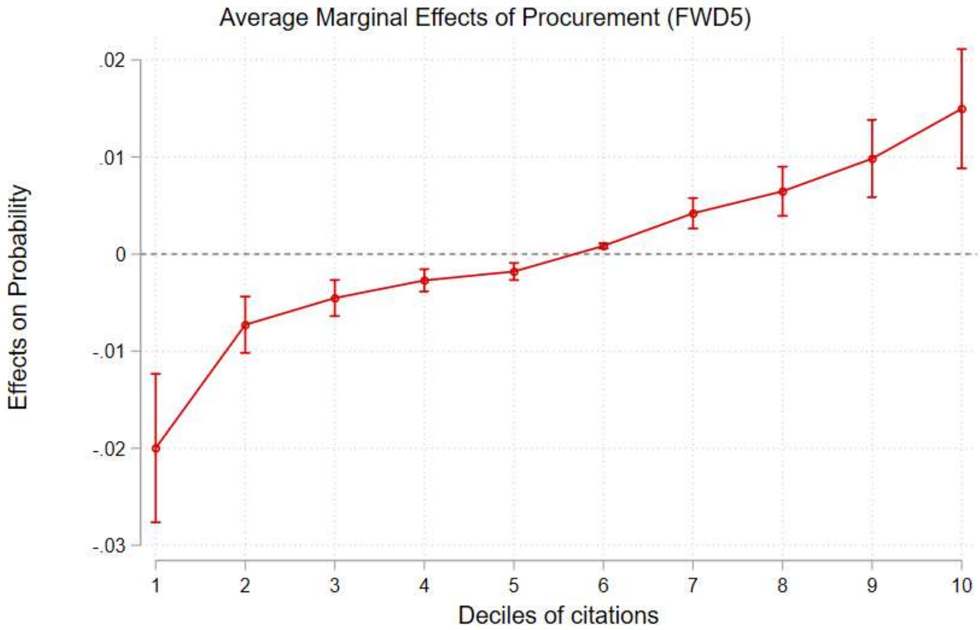
Figure B.6 reports the margins (difference in probability) for government supported patents along the decile of the citation distribution drawn by jointly considering treated and non-treated patents. The results of the ordered logit regression using the same control variables of the previous regressions, but discarding applicant fixed effects and controlling instead for the size of the patent portfolio of a given applicant,[4] confirm the descriptive evidence.

Figure B.5: deciles of 5 year forward citations, sponsored and non-sponsored patents.



[4] We do not include applicant fixed effects in this latest estimation because of the potential issue they can bring with in non-linear models.

Figure B.6: Average marginal effect of government sponsored R&D.



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