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Knowledge spillovers from clean and dirty technologies*

Antoine Dechezleprêtre† Ralf Martin‡ Myra Mohnen§

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Abstract

Government policy in support of innovation often varies across technology areas. An important example are climate change policies that typically try to support so called clean technologies that avoid greenhouse gas pollution and hamper dirty technologies that are associated with polluting emissions. This paper explores the economic consequences of such policy moves in the short run. At the margin private returns of R&D investments in different areas should be equalised. Hence, shifting the composition of R&D activities by a policy intervention will only have a meaningful impact on economic outcomes if the external returns differ. Hence, we compare innovation spillovers between clean, dirty and other emerging technologies using patent citation data. We develop new methodology including the usage of Page rank measures developed by Google to rank web content. Exploring a wide range of robustness checks we consistently find up to 40% higher levels of spillovers from clean technologies. We also use firm-level financial data to investigate the impact of knowledge spillovers on firms' market value and find that marginal economic value of spillovers from clean technologies is also greater.

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1 Introduction

It is commonly recognized that knowledge spillovers from innovative activities provide a case for government intervention in the market because private R&D investments are likely too low. It has also been recognised that not all innovations create spillovers to the same extent. In particular more basic research is assumed to create stronger spillovers and therefore should attract more government support. However, for better or worse governments often champion specific technology areas – rather than types - such as defence, IT, aerospace, bio technology etc. Often this is because a certain area promises auxiliary – i.e. not necessarily economic – benefits such as security, health or simply prestige. If the degree of spillovers that is generated by these different areas are the same, then – from an economic point view – we don't need to worry about this. However, if there spillovers vary substantially across areas the distribution of government intervention can affect the level and growth of economic well being. To the best of our knowledge this study is the first to systematically compare spillovers between different technology areas. Our main focus is what we have dubbed dirty and clean technologies; i.e. technologies that are associated with GHG gas pollution and alternative technologies that can replace them. However, we also examine other emerging technologies and we develop methodology that will be relevant to comparing spillovers between technology areas more widely. We focus on clean and dirty technologies because they are an important example of deliberate differential treatment of technology areas by government policies. Increasingly, governments are deployment carbon pricing policies which incentivise clean and hamper dirty technology development. This includes carbon and energy taxes (Aghion et al 2016) but also direct subsidies for clean innovation. In 2012, OECD countries spent over 3 billion euros to support the development of new clean technologies such as renewable energy or hydrogen cars (reference?). The motivation for this is the desire to mitigate climate change in the long run. However, many policy makers – often in an effort to make climate change policy attractive to the public - have suggested that this could also have a beneficial impact on economic outcomes such as growth or employment in the short run. Theoretically, this can only be the case if clean technology innovation leads to larger spillovers than the dirty technology innovation that it replaces. Hence, the main objective of this paper is to measure and compare the amount of knowledge of spillovers from clean and dirty technologies.

Following a long tradition in the literature, we derive our measure of knowledge spillovers from patent citation data (Trajtenberg (1990); Caballero and Jaffe (1993); Jaffe and Trajtenberg (1999); Hall et al. (2005)) although we go beyond the usually used citation count measures.

Patent documents offer a paper trail of knowledge flows as inventors are required to reference previous patents which have been useful for developing the new knowledge described in the patent. Patent citations are not without limitations, but an important advantage of our dataset is that it allows us to deal with most of the problems usually associated with their use. For example, we can identify (and discard) self-citations by inventors, as well as citations added by patent examiners, which might not capture external knowledge spillovers. We rely PATSTAT a new dataset assembled by the European Patent Office in collaboration with the OECD. It provides information on nearly all patents filed worldwide in almost all national patent offices. It also provides information on patent families; i.e. when the same innovation is filed repeatedly in different jurisdictions. This allows us to use an innovation, rather than a patent as the unit of analysis avoiding any double counting. Our main analysis focuses on two technology fields - cars and energy generation - and within each field on two main areas: fossil fuel based technologies (dirty) and alternative (clean) technologies. Cars and power generation account for about 40% of global carbon emissions (IPCC, 2007) They also allow an easy distinction between dirty - i.e. everything related to fossil fuel combustion - and clean - i.e. alternative technologies such as electric vehicles and solar power generation. As an extension we also consider "grey" technologies; i.e. innovation to improve the pollution efficiency of fossil technologies, although this is harder to classify.

There are a variety of confounding factors that might lead to differences in citatations between technology areas such as clean and dirty that are un-related to spillovers in an economic sense. Citations in patent documents are driven by legally binding definitions on what constitutes prior art. These differ over time and between jurisdictions. Citation behaviour might also vary over time because of technological developments such as the

Clean and dirty innovations are not uniformly distributed neither across space nor time. Hence, average citation counts for the two technology areas might differ for example because one areas tends to be filed more with patent offices that require more citations. We address a wide range of such concerns by including a wide set of control variables such as patent office by year fixed effects.

However, this will not deal with variation in citation practice between different technological areas; e.g. suppose that in some technological areas it is customary to cite more frequently by explicity referring to more remote underlying ideas. Because most innovations receive their citations from within their own technological area, this could lead to differences in citation numbers that reflect "cultural" differences between technological fields rather than than economically meaningful spillovers. We address this in two ways. Firstly, we examine spillovers differences relying only on citations outside an innovation's technoligcal area. Secondly, we the Page-rank measures of an innovation rather than the mere citation count. The Page-rank was developpped by Google's Larry Page to rank the relevance of webpages on the basis of how they are hyperlinked; i.e. cited. We are one of the first to apply this to patent data. It is recursively computed as the weighted average of all citing patent page ranks weighted by the inverse ratio of citations in a citing patent.[1] Hence, a patent receives a high page rank if it is cited by many other patents that are themselves cited a lot but do not cite many others themselves. This not only deals with potential variation in citation cul-

[1]We discuss this in more detail below.

ture between technological areas but also considers indirect spillovers; i.e. an innovation can create spillovers because it is cited a lot by itself or because it is cited by another innvation that is cited a lot.

Our results suggests that clean innovations generate singificantly more knowledge spillovers than their dirty counterparts. All other things being equal, clean patented inventions receive 43% more citations than dirty inventions. The gap is larger in the electricity production sector (49%) than in the transportation sector (35%). Interestingly, the gap between clean and dirty technologies has been constantly increasing during the past 50 years. We show that clean patents are not only cited more often, they are also cited by patents that are themselves cited more often (irrespective of their technological area). When considering our new PatentRank index, we also find strong evidence of larger spillovers from clean technologies. Our conclusions are robust to a large number of sensitivity tests. These include discarding citations added by patent examiners, correcting for self-citations at the applicant level, including inventor fixed effects, looking at different subsamples and including additional control variables.

How can we account for the larger knowledge spillovers from clean technologies? One explanation stands out from our investigation: clean technologies seem to benefit from steep learning curves associated with new technological fields. [2]When we control for the age of the technology, the clean premium decreases by 14%. We then compare knowledge spillovers between clean, grey and "truly dirty" innovations. The analysis suggests a clear ranking: clean technologies exhibit significantly higher levels of spillovers than grey technologies, which themselves outperform truly dirty technologies. We also compare clean inventions with other emerging technologies such as biotechs, IT, nanotechnology, robot and 3D, and find that clean patents appear much closer in terms of knowledge spillovers to these radically

[2]We partially control for this by including a measure of previous patenting within the technology class of a given patent in our regressions, but this novelty effect might not be well captured by the number of patents.

new fields than to the dirty technologies they replace. Interestingly knowledge spillovers from clean technologies appear comparable in scope to those in the IT sector, which has been the driver behind the third industrial revolution. When comparing clean, dirty and emerging technologies to all other inventions patented in the economy, we find a clear ranking in terms of knowledge spillovers: dirty technologies have lower knowledge spillovers than the average invention, while clean and other emerging technologies exhibit larger knowledge spillovers. With the exception of biotechs, all other emerging technologies (IT, nanotechnology, robots and 3D) show larger knowledge spillovers over the average invention than clean inventions. Taken together, these pieces of evidence suggest that the clean advantage might be a feature of the radical novelty of the field.

We make every effort to control for confounding factors in citation behaviour between clean and dirty technologies. However, with patent and citation data alone we cannot infer anything about the actual economic value of innovations and their spillovers. This could be a problem if - say - dirty spillovers generated vastly more economic value per innovation than clean spillovers which could imply that the economic relevance of dirty spillovers is higher despite their lower frequencey as measured by citations. For a subset of our data we can address by expanding an approach first introduced by Hall et al. (2005); i.e. we look at the stock market values (Tobin's Q) of firms taking out patents. Specifically, we examine if the value of a new innovation on a firm is higher if the innovation is benefitting from a dirty as opossed to a clean spillovers. However, our results suggest the opposite: a firm's value increase from a new innovation is higher when benefiting from more clean spillovers. Hence, this re-inforces the spillover advantage of clean technologies.

Our results have a number of immediate implications. Firstly, they highlight that there large and economically relevant spillover differences between technology areas and therefore a meaningfully growth policy design should take these into account.

Secondly, with respect to climate change policy, our findings provide support for the idea that pollution pricing should be complemented with specific support for clean innovation—e.g. through additional R&D subsidies—that goes beyond standard policies in place to internalize knowledge externalities. Indeed, the higher spillover effects from clean innovation compared to dirty innovations (including "grey" energy efficiency technologies) uncovered in this paper justify higher subsidies to clean R&D in a first best policy setting. Radically new clean technologies should receive higher public support than research activities targeted at improving on the existing dirty technologies. However, such specific support could equally be justified for a range of other emerging areas, such as nanotechnologies or IT. Therefore our results go some way into supporting the recommendation by Acemoglu et al. (2012) that only clean (and not dirty) technologies should receive R&D subsidies.[3]

Thirdly, our results lend support to the idea that a redirection of innovation from dirty to clean technologies reduces the net cost of environmental policies and can lead to higher economic growth in the short run, if the benefits from higher spillovers exceed these costs. Indeed, if the factors leading to an under-provision of knowledge are more severe for clean technologies and if new clean technologies are induced by environmental regulation, environmental policies could generate growth by unintendedly correcting a market failure that has been hampering the economy, irrespective of the environmental problem (Neuhoff (2005)). In fact, the presence of a market failure associated with R&D spillovers from clean innovations is one of the possible theoretical foundations for the Porter hypothesis (Porter and Van der Linde (1995)) according to which environmental regulations may enhance firms' profits and competitiveness (see Ambec et al. (2013) and Ambec and Barla (2006), for a recent review). For example, in Mohr (2002), the existence of knowledge spillovers prevents the replacement of an old polluting technology by a new, cleaner and more productive technology, as

[3]Interestingly, though, for a reason that is not present in their model: Acemoglu et al. (2012) do not assume different spillovers from clean and dirty technologies. The crucial assumption on which the results by Acemoglu et al. (2012) hold is that patents last only for one period. Greaker and Heggedal (2012) show that it is possible to obtain similar results when relaxing this assumption if one now assumes that clean technologies exhibit larger knowledge spillovers than dirty technologies.

firms have a second-mover advantage if they wait for someone else to adopt. The introduction of an environmental regulation induces firms to switch to the new, cleaner technology. This simultaneously improves environmental quality and eventually increases productivity. Our results however suggest that the potential growth effects of environmental policies very much depend on the type of displacement being induced by increasing support for clean technologies. If this leads to less investment in dirty technologies, as evidenced by Aghion et al. (2012), there seems to be scope for medium run growth effects. If innovation in other emerging areas is crowded out, such effects are less likely.

Our results also have implications for the modeling of climate change policy. For example, Fischer and Newell (2008); Fischer et al. (2013) assess different policies for reducing carbon dioxide emissions and promoting innovation and diffusion of renewable energy, with an application to the electricity sector. They model R&D investments and learning-by-doing, but assume that knowledge spillovers have the same intensity across clean and dirty technologies. Our paper suggests that this assumption does not hold in practice and provides estimated parameters that can be used to more precisely model the difference between clean and dirty technologies.

Our paper relates to three main strands of the literature. First, our work draws on the extensive empirical literature that has used patent data to analyze the determinants and the effects of knowledge spillovers. Pioneers of patent citation data as a measure of knowledge spillovers include Scherer (1965) and Schmookler (1966). Griliches et al. (1991); Griliches (1992) survey this earlier literature. Since then, a large number of papers have used this method to investigate knowledge diffusion (see, among others, Trajtenberg (1990); Caballero and Jaffe (1993); Hall et al. (2001)). In particular, many papers have focused on the geography of knowledge spillovers (Jaffe et al. (1993); Jaffe and Trajtenberg (1996, 1999); Thompson and Fox-Kean (2005)).

Second, in the energy literature some papers have recently attempted to compare knowledge spillovers from energy technologies with those of non-energy technologies. Bjørner and Mackenhauer (2013) compare the spillover effects of private energy research with those of other (non-energy) private research. They find that spillover effects of energy research may be lower than for other types of private research. Popp and Newell (2012) use US patent citation data to compare the social value of alternative energy patents to that of other patents filed by the same firms. They find that alternative energy patents are cited more frequently by subsequent patents, and by a wider range of technologies, than other patents filed by the same firms. However, none of these papers distinguishes between clean and dirty technologies within energy technologies.

Third, our paper is closely related to the literature on the impact of environmental policies on economic growth, which is itself rooted in the endogenous growth literature (for seminal contributions, see Romer (1990); Aghion and Howitt (1992, 1996, 1998); Grossman and Helpman (1991)). Smulders and De Nooij (2003) introduce a difference in spillovers from the clean and the dirty sector into a model in which both the rate and direction of technological change are endogenous. They discuss the implication of this difference for growth in the long run. In a Schumpeterian growth model where new technologies are both more productive and more environmentally-friendly, Hart (2004) shows that environmental policy can stimulate economic growth (see also Hart (2007); Ricci (2007b), for similar types of models, and Ricci (2007a), for a review of this literature).

The remainder of the paper is organized as follows. In the next section we present the datasets, explain how we measure knowledge spillovers and conduct some preliminary data exploration. In section 3, we discuss our empirical strategy in greater detail. Section 4 reports our main results. In section 5, we estimate the market value of clean knowledge spillovers. We discuss the implications of our findings in the final section.

2 Data and descriptive statistics

2.1 The patent database

We use data from the World Patent Statistical Database (PATSTAT), maintained by the European Patent Office (EPO). PATSTAT includes close to 70 million patent documents from 107 patent offices. We identify clean and dirty patents using the International Patent Classification (IPC) and the European Patent Classification (ECLA). For this purpose we rely heavily on work carried out at the OECD and the EPO, which has recently developed a patent classification scheme for "Technologies related to climate change mitigation and adaptation" (see Veefkind et al. (2012) for more information on how this scheme was constructed).[4]

We focus on two sectors where we can precisely distinguish between clean and dirty patents: electricity production (renewables vs. fossil fuel energy generation) and automotive (electric and hydrogen cars vs. internal combustion engines). Our paper rests primarily on a distinction between radically clean innovations (electric cars, solar energy...) and their dirty counterparts (gasoline-fueled cars, coal-based electricity generation...). However, an important feature of the dirty category is that some patents included in this group aim at improving the efficiency of dirty technologies (for example motor vehicle fuel efficiency technologies), making the dirty technology less dirty. We refer to these energy-efficiency patents as “Grey” inventions. The list of patent classification codes used to identify clean, dirty and grey inventions is shown in table 20 and 21.

Given that the same invention may be patented in several countries, our level of observation is the patent family (the set of patents covering the same invention in several countries). In

[4]This new scheme was defined with the help of experts in the field, both from within and outside the EPO, including from the Intergovernmental Panel on Climate Change (IPCC). It brings together technologies related to climate change that are scattered across many IPC sections and includes around 1,000 classification entries and nearly 1,500,000 patent documents.

Table 1: Number of clean and dirty inventions by sector

Sector	Clean	Grey	True Dirty	Total
Transport	74,877	133,083	212,193	420,153
Electricity	103,659	19,827	627,590	751,076
Total	178,536	152,910	839,783	1,171,229

other words, we treat multiple filings of an invention as one invention and count citations by patent family instead of individual patents.[5] In total, our sample spans from 1950 to 2005[6] and includes over 1 million inventions with approximately 3 million citations made to these inventions. A breakdown of the number of inventions in each sector can be found in table 1. Clean inventions represent around 15% of our sample.

2.2 Citation counts as knowledge spillovers

Patent data has a number of attractive features. First, patents are available at a highly technologically disaggregated level. This allows us to distinguish between clean and dirty innovations in several sectors, in particular electricity production and transportation. In comparison, R&D expenditures of a car company cannot usually be broken down into clean and dirty innovations. Second, patent documents contain citations to "prior art" as inventors are required to reference previous patents that have been used to develop the new technology described in the patent. Citations are a response to the legal requirement to determine the scope of an inventor's claim to novelty and thus represent a link to the pre-existing knowledge upon which the invention is built. [7]In other words, a citation indicates that the knowledge

[5]A patent family is considered clean if at least one patent within the family is clean

[6]We stop in 2005 to allow at least five years for patent to get cited. The majority of citations occur during the first five years of a patent.

[7]US patent law 37 C.F.R 156 establishes that 'each individual associated with the filing and prosecution of a patent application has a duty of candour and good faith in dealing with the (US Patent) Office, which includes a duty to disclose to the Office all information known to that individual to be material to patentability [...] no patent will be granted on an application in connection with which fraud on the Office was practiced or attempted or the duty of disclosure was violated through bad faith or intentional misconduct'.

contained in the cited document has been useful in the development of the new knowledge laid out in the citing patent and thus represents a knowledge flow (Collins and Wyatt (1988)). It is therefore not surprising that patent data have been widely used in empirical studies of knowledge spillovers (Jaffe et al. (1993); Jaffe and Trajtenberg (1999); Keller (2004); Caballero and Jaffe (1993); Jaffe and Trajtenberg (1996)).

To give a concrete example of knowledge spillovers, take the patent entitled "X'Ray Apparatus" (US8036340B2, see figure 8). It was applied for in 2008, published in 2011 and belongs to the H05K class of electric techniques. The patent documents the inventor(s), and the applicant of the invention as well as their addresses. It also lists the claims of the invention and references other patents which will be useful in the making of the invention, including whether these citations were added by the examiner or not. Among its references, it lists a patent US6727670B1 entitled "Battery Current Limiter for a High Voltage Battery Pack in a Hybrid Electric Vehicle Powertrain" (see figure 7) which was published in 2004. It belongs to the "electric motor" class (H02P). The citation received represents a transfer of knowledge. Looking in turn at the list of reference, it cites the patent US6026921A ("Hybrid Vehicule Employing Parallel Hybrid System, using both Internal Combution Engine and Electric Motor for Propulsion", see figure 6) which was published in 2000 is classified as B60K which falls under our clean transport category. This represents a clean knowledge spillover.

For each patent family in our dataset, we compile all the citations received regardless of their

In contrast, the EPO has no requirement similar to the duty of candour. Rule 42 of the European Patent Convention requires that the description in a European patent application should 'indicate the background art which, as far as is known to the applicant, can be regarded as useful to understand the invention, draw up the European search report and examine the European patent application, and, preferably, cite the documents reflecting such art'. The different legal requirements of the two systems have implications both in terms of who adds the citations and in the number of citations in the patents. For EPO patents, it is the patent office's examiner rather than the inventors or applicants who adds the majority of patent citations. This implies that in the EPO system, inventors are more likely to be unaware of the patents that are (ultimately) cited in their patents. However, citations in EPO patents may be less 'noisy' than USPTO citations, since it can be assumed that they have been scrutinised and chosen by the patent examiner, and citing-cited patent pairs might be 'closer' both in time and technological content than those extracted from the USPTO [Breschi and Lissoni (2005); Michel and Bettels (2001)] field and whether or not they are clean.

Nevertheless, there are a few drawbacks to bear in mind. Patent citations are an incomplete measure of knowledge flows because they only capture flows that result in a novel and patentable technology. For this reason Griliches (1992) refers to citations as "pure knowledge spillovers". Since not all inventions are patented, patent citations underestimate the actual extent of knowledge spillovers. Other channels of knowledge transfers, such as non-codified knowledge and embodied know-how (inter-firm transfer of knowledge embodied in skilled labor, knowledge flows between customers and suppliers, knowledge exchange at conferences and trade fairs, etc.) are not captured by patent citations. It is however reasonable to assume that knowledge spillovers within and outside the patent system are correlated. Furthermore, there is a consensus that patent citations are a noisy measure of knowledge flows (Jaffe et al. (2000)). First, citations made to patents by the same inventor (refered to as self-citations) represent transfers of knowledge that are mostly internalized, whereas citations to patents by other inventors are closer to the true notion of diffused spillovers. However, this problem can be (at least partly) resolved by excluding self-citations by the inventor. Second, some citations are added by patent examiners during the examination process (see Cockburn et al. (2003) for an overview of the process). In a survey of inventors, Jaffe et al. (2000) show that the influence of examiners on citations is considerable, and that inventors were fully aware of less than one-third of the citations on their patents. Alcacer and Gittelman (2006) find that examiners are responsible for 63% of citations on the average patent, and that 40% of patents have all citations added by the examiners.[8] These types of citations might not capture pure

[8] Alcacer et al. (2009) utilise a change in the reporting of US patent data that allows to separate citations added by the inventor and the examiners to examine the examiners' behaviour with respect to inventor citations. In the first case, the patent examiner might add citations that differ in nature from the inventor/applicant citations ('gap-filling'). Statistically, the gap-filling scenario would bias estimates of inventor knowledge. In the second case, the examiner might add similar citations ('tracking'). Tracking does not lead to any bias but it may cause standard errors in statistical estimations to be inflated. This raises doubts about patent citations as good indicators of knowledge flows. If examiner and inventor citations resemble each other closely, this suggests that firms and inventors choose their citations with respect to potential infrigement and holdup threats and anticipate with some error citations most likely to be added by exam-

knowledge spillovers if the inventor was genuinely unaware of that invention.[9]Fortunately, our patent data indicate whether the citations was included by the applicant or the patent examiner. We can thus check the robustness of our results to excluding citations added by patent examiners.[10] Third, inventors and applicants might be strategically referencing prior art. Citing more prior art will make a patent more valuable in litigation, as it is much harder to prove a patent is invalid if the patent office has already considered it and rejected the relevant prior art (Allison et al. (2003)). Most firms employ patent attorneys - many of whom were formerly patent examiners - to maximise the chances of approval by the examiner in order to avoid potential infringement and costly holdups. However, inventors have an incentive not to cite patents unnecessarily as it may reduce their claims to novelty and therefore affect the scope of the monopoly rights granted by the patent (Hegde and Sampat (2009); Sampat (2005)). Moreover, not properly referencing priori art can lead to the invalidation of the patent and is therefore a dangerous strategy.[11]

2.3 A new measure of spillovers: PatentRank

A potential concern with citation counts is that a citation from an obscure patent is given the same weight as a citation from a highly-cited work. Hence it is possible that some patents receive less citations than others but are cited by patents that are themselves more influential (i.e., more cited themselves). In particular many ground-breaking patents are modestly cited

iners. Moreover, examiners and inventors might exchange information during the application process, and examiners themselves are prone to biases in favour of citing particular patents. Using the EPO data which allows to identify the source of the citations since 1979, Criscuolo (2006) attempt to identify the factors that influence whether an observed patent-to-patent citation was added by the applicant/examiner.

[9]Of course, if the inventor has deliberately omitted to cite a relevant invention, then citations added by patent examiners actually capture true knowledge spillovers.

[10]Note that even if the citations was added by the inventor, s/he might have learnt about the cited invention only after the development of the invention. We have no way to control for this potential isssue.

[11]"Failure of a person who is involved in the preparation or prosecution of a United States patent application to disclose material prior art can result in the patent not issuing, or if issued, being held unenforceable or invalid. As in many instances, the issue of whether prior art is material to patentability can be quite subjective; it is critical that inventors, assignees, and attorneys be acquainted with the obligations to disclose such prior art." (Silverman (2003a)

due to the small size of the scientific community in their area at the time of the publication, but subsequent patents are themsleves increasingly cited (Maslov and Redner (2009)).

In order to take into account the whole network of patent citations, we apply the random surfer PageRank algorithm (Page et al. (1999)) to our patent dataset. This algorithm was originally used by the web search engine Google to help determine the relevance or importance of a webpage. It does so by analyzing the network of hyperlinks of web pages. The basic idea is that a webpage is considered important if many other webpages point to it, or if many webpages point to the webpages that point to it (or both), and so on. To date, a handful papers have applied this method to rank the importance of patent documents (Lukach and Lukach (2007); Shaffer (2011)). The resulting PatentRank has the advantage to readily identify patents that are modestly cited but nevertheless contain ground-breaking results. It also normalizes the impact of patents from different areas allowing for a more objective comparison (Maslov and Redner (2009)).

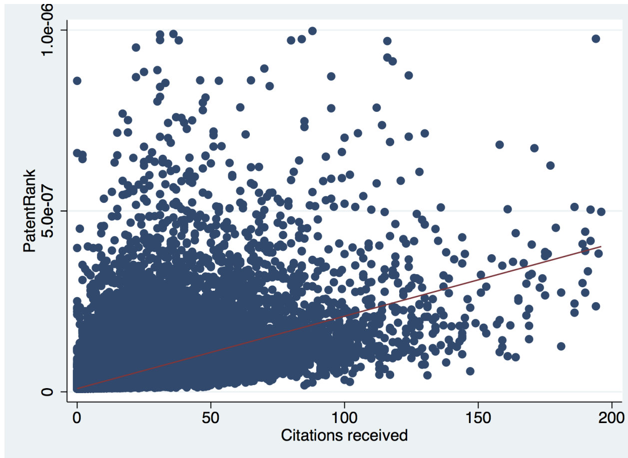
The PatentRank of a patent i is defined as the weighted sum of PatentRanks of all patents citing i, where the weights depend on the number of citations *made* by these citing patents. Therefore, a patent has a high rank if it is cited by many patents with a high rank, and it is better to be cited by a patent that cites only one patent than by a patent that has a long list of references. The PatentRank $r(i)$ of patent i is defined according to the following formula and is computed recursively:[12]

$$r(i) = \frac{\alpha}{N} + (1-\alpha) \sum_{j \epsilon F(i)} \frac{r(j)}{B(j)}$$

where N is the total number of patents, $F(i)$ is the set of patents that cite patent i (i.e. patent i's "forward citations"), and $B(j)$ is the number of citations made by patent j (i.e.

[12] The process converges very quickly. In practice we use 50 iterations but the process converges after just a few iterations.

Figure 1: Citation counts and PatentRank



patent j's number of "backward" citations). The parameter α, the damping factor, is used to avoid sink patents (i.e. patents that are never cited) because sink patents will lead to an endless loop.[13]

When constructing the PatentRank, we use the entire population of inventions and their citations correcting for self-citations by the inventor. We give inventions that are never cited the smallest PatentRank and rank these PatentRanks to create a PatentRank index. Thus the higher the PatentRank the greater impact or relevance of the invention. Figure 1shows that there is a positive correlation overall between the citation count and the PatentRank but also a vast heterogeneity: many patents have few citations but a high PatentRank and vice versa. As opposed to citation counts, PatentRank allows us to capture the network centrality and in particular the influence of a patent. Hence, both indicators are complementary measures of the intensity of knowledge spillovers.

[13]The mechanism behind the ranking is equivalent to the random-surfer behavior, a person who surfs the web by randomly clicking links on the visited pages but periodically gets bored and jumps to a random page altogether. Therefore, when a user is on a web page, she will select one output link randomly with probability α or will jump to other webpages with probability $1-\alpha$. It can be understood as a Markov process in which the states are web pages, and the transitions are all equally probable and are the links between webpages.

2.4 Exploratory data analysis

The objective of this paper is to compare the extent of knowledge spillovers that arise from clean and dirty innovations. As shown in table 2, aggregating both sectors together, clean inventions receive on average 3.40 citations throughout their life time while dirty inventions receive on average 2.30 citations. This difference is highly statistically significant (see column 3). An obvious problem with this simple comparison is that clean patents are relatively newer, and hence have had less time to be cited. The average age of clean patents (the time between the publication year and today) is 22 years as opposed to 27 years for dirty patents. In order to partly deal with this truncation issue, we look at the number of citations received within the first five years of the patents' publication (Hall et al. (2001)). The difference between the number of citations received by clean and dirty inventions increases: clean patents receive 74% more citations than dirty patents within their first five years. Clean inventions also have a significantly higher PatentRank index than dirty inventions. Looking separately at each technological field, we find that the mean number of citations and the differences between clean and dirty patents vary across sectors. Inventions in the transportation sector are more cited overall and have a higher PatentRank. Clean inventions are more cited and have higher PatentRank than dirty ones in both sectors and this difference is always significant.

The "innovation flowers" in figure 2 show a network diagram for a random sample of 1000 clean and 1000 dirty innovations where the edges represent citations. This visual representation of PatentRank highlights the greater PatentRank of clean inventions.

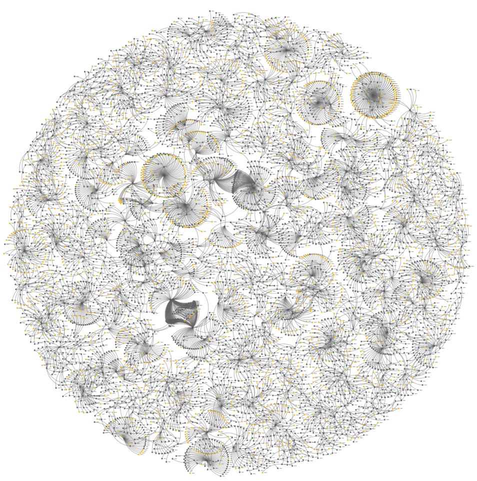
Table 2: Mean number of citations and PatentRank

	Clean	Dirty	Diff.
	Transport and Electricity		
Citations received	3.399	2.295	1.104***
	(8.256)	(5.921)	[0.016]
Citations received within 5-years	1.807	1.066	0.741***
	(4.754)	(3.109)	[0.009]
PatentRank index	2,335,270	1,920,395	414,874.3***
	(3,019,924)	(2,813,827)	[7,354.756]
	Transport		
Citations received	4.275	3.215	1.060***
	(9.626)	(7.185)	[0.031]
Citations received within 5-years	2.572	1.651	0.920***
	(5.903)	(4.174)	[0.018]
PatentRank index	2,645,597	2,429,006	216,591.2***
	(3,081,718)	(3,126,471)	[12,455.71]
	Electricity production		
Citations received	2.800	1.839	0.961***
	(7.092)	(5.091)	[0.018]
Citations received within 5-years	1.281	0.767	0.514***
	(3.681)	(2.312)	[0.009]
PatentRank index	2,119,068	1,666,122	452,945.3***
	(2,922,871)	(2,633,157)	[8,948.939]

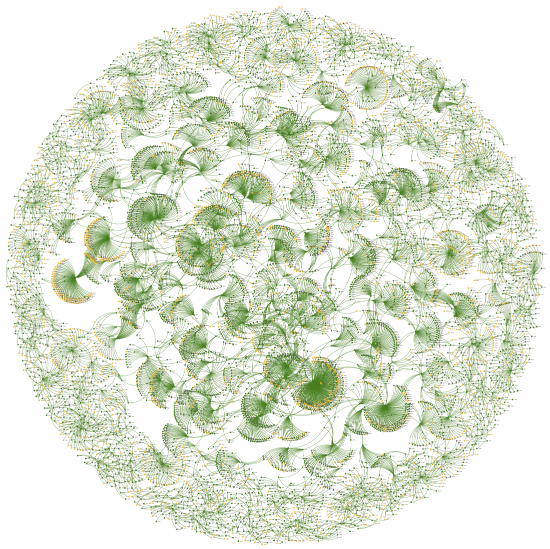
Notes: The first two columns report the mean values with standard deviation in parentheses. The last column reports a t-test for the difference in means with standard error in parentheses. *** indicates significance at 0.1% level.

Figure 2: Innovation Flowers

(a) Dirty



(b) Clean



Notes: The figures visualize innovation spillovoers. We draw a random sample of 1000 dirty and 1000 clean innovations corresponding to the nodes in the figures. The edges correspond to backwards citations. An interactive version is under http://www.eeclab.org.uk/forcedirect_arx.html?tojson_dirlinks0_1995_15_1000_0.json and http://www.eeclab.org.uk/forcedirect_arx.html?tojson_dirlinks0_1995_15_1000_2.json.

3 Methods

The simple comparison of reported in the previous section might be confounded by a range of issues. For example, in recent years there has been a sharp increase in both patenting and citations. This could reflect a genuine increase in economically relevant spillovers; e.g. improved IT systems make it easier to learn about previous inventions. However, it could also reflect legal changes on what consitutes prior art. A similar argument applies when it comes to innovations from different patent offices. When pooling innovations from different years there is also a truncation issue: more recent innovations had less time to generate spillovers than older ones. Most clean innoation activity occured in more recent years. Clean innovation activities are also more prevalent in some countries than in others. Hence, such factors might confound any genuine clean effects.

Our strategy to account for this is to estimate a simple count data model of the type

$$C_i = exp(\beta Clean_i + \gamma X_i + \epsilon_i) \tag{1}$$

where C_i is the number of citations received by invention i (excluding self-citations) or the PatentRank index associated to invention i, $Clean_i$ is a dummy variable indicating whether invention i is clean, X_i are controls and ϵ_i is the error term. Our sample is the population of clean and dirty patents. Hence, the main coefficient of interest, β, captures the percentage difference between the number of citations received by clean and dirty patents, all other things being equal. Given the count data nature of the dependent variable, we estimate Equation 1 by Poisson pseudo-maximum likelihood. We include a number of control variables to purge the estimates from as many potential confounding factors as possible which we discuss in more detail below. However, our basic set of contol variables includes patent office[14]-by-year-by-sector[15] fixed effects. [16]

Implicit in the formulation in equaition 1 is the idea that every citation creates economic value by inspiring a new innovation. It is instructive to express the total spillover value SV_i of an innovation i as follows:

$$SV_i = \sum_{j \in J(i).} \phi_{ji} \left(PV_j + SV_j \right) \tag{2}$$

where $J(i)$ is the set of innovations that could potentially be influenced by innovation i - i.e. all innovations coming after i - PV_j is the private and SV_j the spillvoer value of an innovation j. ϕ_{ji} is the fraction of j's value that can be attributed to innovation i. By merely looking at citation counts as in equation 1 we make the assumption that $\phi_{ij} = 1$ if j cites i (and zero otherwise). Moreover we assume that the private values PV_j are identical across innovations. Clearly these are rather strong assumptions although it might be entirely possible that any error introduced when they are not met is entirely orthorgonal to the question of a clean spillover gap. To be sure we will relax these assumptions in a number of ways as discussed in more detail in the following.

[14]For innovations that are patented in multiple countries, we use the patent office where the patent was patented first.

[15]i.e. energy generation or automotive.

[16]This is implemented following Hausman et al. (1984) by the xtpoisson, fe command in STATA which is the count data equivalent to the within groups estimator for OLS. Note that Poisson models estimated by pseudo-maximum likelihood can deal with over-dispersion (see Silva and Tenreyro (2006)), so that negative binomial models offer no particular advantage. In particular, we find the pseudo-fixed effects negative binomial estimator available in stata (xtnbreg, fe) untrustable, since it does not truly conditions out the fixed effects (only the overdispersion coefficient is assumed to vary across units - see Allison and Waterman (2002); Greene (2007), for more information on this issue). However, as a robustness check we also estimated Equation (1) using an unconditional negative binomial estimator with patent office, year, month and sector dummies (including a whole range of sector by year by patent office dummies is computationally infeasible) and find very similar results.

3.1 Patent Rank

We develop a new method of measuring spillovers in patent data which we call Patent Rank as it is inspired by the Page-rank algorithm - i.e. the method to rank hyperlinked webpages that is at the heart of Google's success as a search engine. This addresses two issues in particular:

Firstly, it will allways be difficult to attribute and value the specific contribution of prior art. However, a reasonable alternative to simply assigning $\phi_{ij} = 1$ is the inverse of the number of citations *by* innovation j:

$$\phi_{ji} = \frac{1}{BC_j}\sigma_i \tag{3}$$

where BC_j are the number of backward citations by innovation j; i.e. if an innovation j cites a lot of other innovations besides i is likely that the contribution of each invididual i is smaller than would otherwise be the case. We also include $\sigma_i < 1$ as a scale factor representing the contribution of spillovers as opposed to other factors such as the firms R&D efforts. Note that the inverse backward citation weighting can be thought of as observationally equivalent to the argument made in the introduction: when comapring different technology fields differences in citations might be driven by a different citation culture where some fields tend to cite more distant aspects of prior art than others. Hence, if j belongs to citation happy field, $i's$ contribution to the value of j is arguably lower. A similar idea is used in the Google pagerank algorithm. A hyperlink to a web page i from a web page j is considered less valuable if j hyperlinks a large number of other pages besides i.

Secondly, note that it is unlikely that the spillover values SV_j are homogenous across innovations. Indeed, our main focus in this study is the heterogeneity of spillovers. By just counting citations we allow spillover values to be heterogenous on the left hand side of equation 2 while pretenting that they are uniform on the right hand side of equation 2. However, equation 2 suggests an immediate solution: it implies a system of linear equations (one for each innovation) which can be solved for the spillover values SV_i. Indeed this is what the page-rank algorithm does as well where citations come in the form of hyperlinks.[17]

While conceptually, the equation system implied by equation 2 is simple, it raises considerable computational issues as we are dealing with tens of millions of equations. However, as is common in Page Rank calculations, the equation system can be solved recursively, rather than by brute force matrix inversion.[18]

One further open question concerns the private value of innovations PV_j . Clearly, it is very likely that these vary considerably across innovations. We make a number of assumptions and examine if this has any impact on our main result of a clean and dirty gap. Firstly, we assume the same value which we derive from a regression of the impact of a new innovation on the stock market value of the innovating firm. We discuss these regressions in more detail below. Secondly, we use common distinctions between high value innovations; e.g. we assign a non-zero value only to innovations that are "triadic"; i.e. an innovation that is patented in at least the US, Europe and Japan.

Finally, we need to make assumptions about the values for σ_i, the contribution of spillovers as opposed to other factors. In our main results we rely on uniform value of $\sigma_i = 0.14$ which we derive from an innovation production function type result as reported in Aghion et al. (2016). The details of this are explained in appendix XXX. However, we also examine the robustness of our results when using other values.

[17] Although, instead of the private values, the page rank algorithm uses the constant probability of hitting a web-page randomly - i.e. the inverse of the number of total webpages.

[18] We implemented the procedure in STATA and can make it available as supplementary material to this paper. We also show in the appendix that none of our modifications to the PageRank algorithm affects its validity.

3.2 Evidence from firm values

In addition to using the Patentrank approach we explore the value of different types of spillover directly by looking at the stock market values of innovating firms. Of course this restricts our sample to the innovations undertaken by stock listed companies. However, this will help us detect some potential violations of the assumption we are making above. For instance, suppose that dirty innovations tend to create knowledge spillovers for innovations with higher private values on average and the drivers of these higher values are not connected to easily observed characteristics.[19] Or, it could be the case that

To address this we built on the work by Hall et al. (2005), according to which a firm's knowledge assets are modeled as being accumulated in a continuously ongoing innovative process where R&D expenditures reflect innovative input, patents record the successful innovations that can be appropriated by the firm, and citations received by the firm's patents (forward citations) measure the relative importance of the patents. We also include citations made (backward citations) as in Deng (2008) as a proxy of spillovers the firm has received, which are considered an additional kind of innovative input to direct R&D spendings on the belief that more knowledge inflows increase the firm's knowledge stock and may boost the firm's R&D productivity. We extend Deng (2008)'s analysis by distinguishing between clean and dirty backward citations.

Consider Griliches (1981)'s market valuation equation

$$V_{it} = q_t(A_{it} + \beta K_{it} + \gamma R_{it} + \eta S_{it}) \tag{4}$$

where V_{it} denotes firm i's stock market value in year t, A_{it} the book value of its physical assets, and K_{it} the knowledge assets. q_t represents the shadow value of firms' assets, and the coefficient b measures the shadow value of knowledge assets relative to physical assets.

[19] Such as the number of patent offices a particular innovation is filed with.

σ measures the scale effects in the value function and is assumed to be one.

Taking the logarithm, we have the following estimation equation:

$$\log Q_{it} = \log(\frac{V_{it}}{A_{it}}) = \log q_t + \log(1 + \beta \frac{K_{it}}{A_{it}}) + \varepsilon_{it} \tag{5}$$

where Q_{it} represents Tobin's q and ε_{it} are the prediction errors.

As Deng (2008), we use the following value function to evaluate the firm's knowledge assets

$$K_{it} = f(R\&D_{it}, BCIT_{it}, \omega_{it}) \tag{6}$$

where $R\&D_{it}$denotes the accumulated R&D spendings, $BCIT_{it}$ the accumulated backward citations the firm has made as a proxy of the knowledge inflows received by the firm, and ω_{it} the accumulated idiosyncratic productivity shocks in the firm's inventive activities. ω_{it} is proxied by the patent / R&D ratio, weighted by the average number of forward citations the firm's patents receive over their entire lives (Hall et al. (2005)). This can be viewed as the knowledge outflow made by the firm.

Taking first-order Taylor expansion of equation 5 yields

$$K_{it} = f_1 \times R\&D_{it} + f_2 \times BCIT_{it} + f_3 \times \frac{PAT_{it}}{R\&D_{it}} + f_4 \times \frac{FCIT_{it}}{PAT_{it}} \tag{7}$$

where PAT_{it} and $FCIT_{it}$ are firm i's patent stock and forward citations stock in year t respectively. Combining equations 5 and 6 leads to

$$\log Q_{it} = \log q_t + \log(1 + \beta_1 \frac{R\&D_{it}}{A_{it}} + \beta_2 \frac{BCIT_{it}}{PAT_{it}} + \beta_3 \frac{PAT_{it}}{R\&D_{it}} + \beta_4 \frac{FCIT_{it}}{PAT_{it}}) + \varepsilon_{it} \tag{8}$$

The coefficient β_2 represents the value of knowledge flows brought by an additional backward citation, and $\frac{\beta_2}{\beta_1}$ is a direct measure of the monetary value of knowledge spillovers in terms of R&D equivalent dollar.

We will estimate equation (9) using a non-linear least square including a full set of year and NACE dummies or firm fixed effects.

Table 3: Basic results

	(1)	(2)	(3)	(4)
Dep. Variable	Citations received		Across Technology citations (IPC3)	Across Technology (Clean vs
Clean invention				
Patent office-by-year-by-sector	no	yes	yes	yes
Obs.				

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations recei
by inventors (columns 1 to 3) and the PatentRank after 20 iterations (columns 4 to 6). All columns are estimated by fixed-effects Poisson pseudo

4 Results

In table 3 we report our basic results for different spillover measures. In columns 1 and 2 we look at simple citation counts. Columns 1 and 2 look at spillovers across technology classes. As discussed above, this addresses the concern that the amount of citations that are included are subject to "cultural" differences in various disciplines. Finally, columns 5 explores our new patent rank measure. We see that in each case there is an advantage of XX to XX % for clean innovations.

What could be the drivers and mechanisms behind the subtantial clean spillover gap? In the following we examine in detail a number of potential reasons.

4.1 Existing and future knowledge stocks

Dirty technologies are still the main driver of most economies. As a consequence knowledge stock in dirty fields are larger as

Table 4: Descriptive statistics on knowledge stocks

	(1)	(2)
	Clean	Dirty
Stock before within IPC2		
Stock before within IPC3		
Stock before within clean/dirty		
Stock after within IPC2	yes	yes
Stock after within IPC3		
Stoack after within clean/dirty		

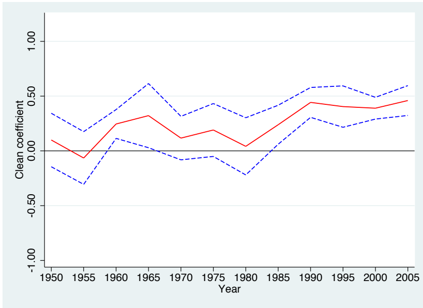
Notes:

Table 5: Controlling for future and

	(1)	(2)	(3)	(4)
Dep. Variable	Citations received		Across Technology citations (IPC3)	Across Technology (IPC2)
Clean invention				
Patent office-by-year-by-sector	no	yes	yes	yes
Obs.				

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations rec self-citations by inventors (columns 1 to 3) and the PatentRank after 20 iterations (columns 4 to 6). All columns are estimated by fixed-effects maximum likelihood.

Figure 3: Clean coefficient between 1950 to 2005 using citations received across IPC3 codes



4.2 Localized knowledge spillovers

4.3 Firm and inventor characteristics

4.4 Government support

4.5 Quality, Originality, Generality

4.6 The clean spillover gap over time

4.7 Direct measurement of the value of clean vs dirty spillovers

4.8 Clean technology as an emerging field?

Table 6: Results by sector

	(1)	(2)	(3)	(4)
Sector	Transport	Electricity	Transport	Electricity
Dep. var.	Citation count		PatentRank	
Clean invention	0.347***	0.488***	0.219***	0.333***
	(0.018)	(0.023)	(0.014)	(0.023)
Number of patents	-0.068***	-0.047***	-0.048***	-0.019**
	(0.008)	(0.009)	(0.006)	(0.007)
Family size	0.070***	0.067***	0.062***	0.060***
	(0.008)	(0.004)	(0.007)	(0.004)
Triadic	0.512***	0.432***	0.279***	0.252***
	(0.056)	(0.050)	(0.045)	(0.041)
Granted	1.134***	0.725***	0.620***	0.381***
	(0.034)	(0.024)	(0.027)	(0.017)
Observations	419,959	748,918	419,959	748,918

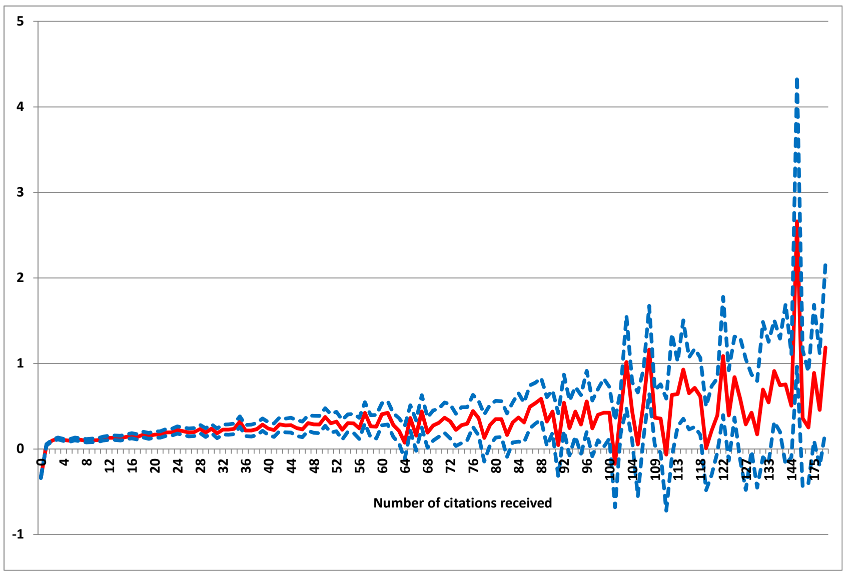
Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variables are the total number of citations received excluding self-citations by inventors in columns 1 and 2 and the PatentRank index in columns 3 and 4. The regressions are all estimated by Poisson pseudo-maximum likelihood. The sample includes inventions from the transport (columns 1 and 3) and electricity (columns 2 and 4) sectors. All columns include a patent office-by-year and month fixed effects.

So far we have focused on the average effect of being a clean invention on the citation outcome. We now investigate the heterogeneity of the clean premium across the distribution of citations. Quantile regression techniques are not readily available for count data models, but we bypass this issue by estimating probit models of the likelihood that a patent falls within a given percentile of the patent citation distribution (see Chernozhukov et al. (2013) for a discussion of this issue). We run the following model:

$$Prob(Cite_i^j = 1) = \alpha + \beta Clean_i + \gamma X_i + \epsilon_i \tag{9}$$

where ${Cite^j}_i$ equals one if invention i receives j citations where j varies between 0 (56% of inventions are never cited) and 479 (the most highly cited invention). $Clean_i$ and X_i are identical to the previous section. Hence the coefficient obtained for $Clean_i$ captures the difference between clean and dirty inventions in the probability of invention i to receive j citations. Figure 4 shows the coefficient obtained for $Clean_i$ and the associated 95% confidence interval on the number of citations received. We conclude from these results that (i) clean inventions are *always* more likely to have a positive citation count than dirty inventions at all levels of the distribution and (ii) the higher intensity of knowledge spillovers from clean technologies is even more pronounced for most highly cited patents.

Figure 4: Heterogeneity



4.9 Localized knowledge spillovers

The existence of localized knowledge spillovers has been widely documented (see Audretsch and Feldman (2004) for an overview). In one of the earliest papers on this subject, Jaffe et al. (1993) show that spillovers from research to firms are more intense when the firm is closer to the institution that generated the research. Jaffe and Trajtenberg (1996, 1999) show that patent citations tend to occur initially between firms that are close to each other, and later on spread to a larger geographical area and other countries. Using European patent data, Maurseth and Verspagen (2002) show that patent citations occur more often between regions which belong to the same country, same linguistic group and geographical proximity (see also Peri (2005)). Similar results have been found for energy technologies (see Braun et al. (2010); Verdolini and Galeotti (2011)).

In our case, clean technologies could generate larger knowledge spillovers than dirty technologies simply because the clean industry might be more clustered geographically than the dirty industry. Although we do not have detailed information on the exact localization of inventors, we do have extensive information on their country of residence. We use this information to distinguish between national (within-border) and international (cross-border) citations. We then separately run regressions on these two sets of citation counts.[20] For the PatentRank, we compute a new PatentRank on the pool of national citations and international separately. We find that clean inventions exhibit larger national (column 2) and international (column 3) spillovers. This suggests that clean inventor community transcend country borders. The clean advantage is larger in terms of domestic spillovers are larger than international ones.

[20] In the case of collaboration, we weight each citations by the number of inventors from each country involved in the invention. For example, three inventors working together, one in country A and two in country B, will count as 1/3 of a citation for country A and 2/3 of a citation for country B.

Table 7: Within vs. across-country spillovers

	(1)	(2)	(3)
Dep. var.	Citations received	Citations received within country	Citations received across country
Clean invention	0.430***	0.423***	0.247***
	(0.014)	(0.017)	(0.019)
Number of patents	-0.057***	-0.057***	-0.081***
	(0.007)	(0.008)	(0.006)
Family size	0.073***	0.062***	0.066***
	(0.004)	(0.003)	(0.004)
Triadic	0.456***	0.363***	0.212***
	(0.036)	(0.028)	(0.040)
Granted	0.947***	0.757***	0.829***
	(0.031)	(0.029)	(0.030)
Obs.	1,149,988	1,149,988	1,149,988

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variables are the total number of citations received (column 1), the total number of citations received from the inventor's country (column 2), the total number of citations received from all countries except the invention's (column 3) corrected for self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

4.10 Public support for R&D

With many clean technologies dependent on policy support of one form or another, the expansion of clean technologies and its spillovers could be due in part to public investment. For instance, in 2011 OECD countries spent over 3 billion euros on R&D support to renewable energy technologies. To control for the government spending level, we include in the first two columns of table 8 the government spending in clean and dirty technologies within the transport and electricity sectors. Since we only have information on R&D spending for 28 countries from 1974 onwards, we run the baseline regression for this sample in columns 1, 3 and 5 and the include the government spending in columns 2, 4 and 6. On average, clean inventions exhibit even larger spillovers than dirty inventions after controlling for government spending. This effect is driven by the electricity production sector.

Another related concern is that research in clean technologies might come disproportionately from universities rather than private firms. If this is the case, the clean premium might come from the fact that university patents are more highly cited and more general (Henderson et al. (1998)). Moreover, the incentive and reward structure within the university system induce scientists to invest in their reputation by making research publicly available (openness of the academic community) and make them more willing to recognize the influence of their predecessors. We control for whether the patent was filed by a university or a firm in the last two columns of Table 8 with private individuals being the baseline and still find that clean inventions receive 42% more citations than their dirty counterpart. Finally we run our baseline regression on the sub-samples of university applicants, firms and individuals. Results are shown in columns 1, 2, and 3 respectively in table 9. In all three cases, clean inventions generate more spillovers than their dirty counterparts. Taken together, these results suggest that public support for R&D is not the driving force behind the clean premium.

Table 8: Public spending

	(1)	(2)	(3)	(4)
Dep. var.	Citations received			
	Government Spending		University	
Clean invention	0.493***	0.507***	0.421***	0.423***
	(0.026)	(0.026)	(0.014)	(0.015)
Number of patents	-0.007	-0.006	-0.047***	-0.050***
	(0.009)	(0.009)	(0.006)	(0.006)
Family size	0.067***	0.067***	0.070***	0.067***
	(0.004)	(0.004)	(0.003)	(0.003)
Triadic	0.452***	0.450***	0.450***	0.432***
	(0.046)	(0.046)	(0.034)	(0.034)
Granted	0.689***	0.688***	1.005***	0.992***
	(0.025)	(0.025)	(0.031)	(0.032)
Government spending		0.034***		
		(0.007)		
University				0.429***
				(0.022)
Firms				0.271***
				(0.018)
Obs.	496,788	496,788	826,078	826,078

Source: International Energy Agency (2013): Energy Technology Research and Development Database (Edition: 2013). Mimas, University of Manchester
Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received excluding self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects. The samples of columns 1 and 2 include patent families for which we have government spending, where column 1 is the baseline and column 2 add a control for government spending. The sample of the last two columns include the patent families for which we have university or firm, where column 1 is the baseline and the column 2 add a control for university and firms.

Table 9: University, firms, and private individuals

	(1)	(2)	(3)
Applicant	University	Firm	Individual
Dep. var.		Citations received	
Clean invention	0.396***	0.418***	0.459***
	(0.003)	(0.016)	(0.030)
Number of patents	-0.100***	-0.041***	-0.068***
	(0.014)	(0.007)	(0.011)
Family size	0.072***	0.067***	0.377***
	(0.005)	(0.003)	(0.042)
Triadic	0.152***	0.454***	-0.870
	(0.043)	(0.035)	(0.613)
Granted	0.775***	1.022***	0.131***
	(0.047)	(0.032)	(0.036)
Obs.	36,186	706,517	75,487

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received excluding self-citations by inventors (columns 1 to 3). The sample includes inventions which have universities (column 1 and 4), firms (column 2 and 5), or individuals (column 3 and 6) as applicants. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

4.11 Network effects

Whether guided by "norms of science" (Merton (1957); Small and Griffith (1974)) or self-interest including personal connections (Leopold (1973); Case and Higgins (2000)), one might be concerned that inventors working on clean innovation behave systematically differently from inventors working on dirty innovations. The community of researchers working on clean technologies could perhaps be smaller and more close-knit. Stuart and Podolny (1996) for instance argue that there is also a strong social component to a citation. The clean premium would then represent inventors' networks rather than true knowledge spillovers. To address this issue we restrict our sample to inventors who have been working both on clean and dirty technologies and include inventor fixed effects in our baseline estimations. Our data includes 41,713 such inventors (representing 2.92% of total inventors). Results are presented in table 10. We similarly introduce applicant fixed effects and the results do not change either. The clean premium remains significant albeit of slightly smaller magnitude. However, this is due to the different sample as can be seen by comparing columns 1 and 2 and columns 3 and 4 respectively.

Table 10: Adding inventor and applicant fixed effect

	(1)	(2)	(3)	(4)
Dep. var.	Citations received			
Clean invention	0.274***	0.336***	0.400***	0.380***
	(0.007)	(0.011)	(0.019)	(0.040)
Number of patents	-0.096***	-0.081***	-0.038***	-0.067***
	(0.004)	(0.006)	(0.008)	(0.010)
Family size	0.038***	0.094***	0.091***	0.100***
	(0.002)	(0.006)	(0.007)	(0.011)
Triadic	0.866***	0.644***	0.461***	0.444***
	(0.012)	(0.026)	(0.056)	(0.089)
Granted	1.234***	1.008***	1.022***	1.000***
	(0.007)	(0.011)	(0.033)	(0.046)
Inventor fixed effect	no	yes	no	no
Applicant fixed effect	no	no	no	yes
Obs.	697,192	697,192	435,584	435,584

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received excluding self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office, sector, year and month fixed effects.

4.12 Nature of the citations

There are two important types of citations: references to patent documents that are particularly close to the new invention, which restrict the claims of the inventor, and references related to the technological background of the new invention. Therefore citations may reflect the similarity of inventions rather than the cumulative nature of innovation (Packalen and Bhattacharya (2012)). To account for the heterogeneous nature of citations, we distinguish between citations received from inventions in the same technological sector (defined using the 3-digit IPC code as assigned by the patent examiner) and citations received from inventions in a different technological sector. [21]While the former include citations which might merely reflect similarities between patents, the latter should be closer to true knowledge spillovers. We then run our baseline regression separately on these two types of citations. Table 11 shows that clean inventions receive more citations both within and across technological fields, suggesting they do generate larger knowledge spillovers in the economy. The PatentRank index is computed on the pool of intrasectoral and intersectoral citations separately.

[21]An important difference between the EPO and the USPTO systems is that in European search reports, cited documents are classified by the patent examiner within a particular citation category according to their relevance. When assessing the novelty of patent applications the examiner searches for earlier documents which have the same or almost the same features as the patent concerned [Schmoch (1993)].

Table 11: Intra vs. inter-sectoral spillovers

	(1)	(2)	(3)
Dep. var.	Citations received	Intra-sectoral citations	Inter-sectoral citations
Clean invention	0.430***	0.457***	0.247***
	(0.014)	(0.015)	(0.019)
Number of patents	-0.057***	-0.053***	-0.081***
	(0.007)	(0.007)	(0.006)
Family size	0.073***	0.074***	0.066***
	(0.004)	(0.004)	(0.003)
Triadic	0.456***	0.487***	0.212***
	(0.036)	(0.036)	(0.040)
Granted	0.947***	0.963***	0.829***
	(0.031)	(0.032)	(0.030)
Obs.	1,149,988	1,149,988	1,149,988

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). s. The dependent variables are the total number of citations (column 1), within a technological field (based on IPC 3 digit code) (column 2), across technological field (column 3) corrected for self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

4.13 Generality and Originality

Clean technologies, being relatively newer, might have more opportunities for "fundamental" research while older dirty technologies might instead be focused on the development of new applications. If clean technologies have more general applications, this might explain why they receive more citations and appear to induce larger knowledge spillovers.

In the previous section, clean inventions were found to be more likely to be cited both within or across their originating technological field. To further investigate the generality of clean and dirty inventions, we construct a measure of generality based on the Herfindahl index of concentration introduced by Trajtenberg et al. (1997). It measures the extent to which the follow-up technical advances (i.e. the citations) are spread across different technological fields, rather than being concentrated in just a few of them (i.e., they are more likely to have the characteristics of a General Purpose Technology, see Bresnahan and Trajtenberg (1995); Popp and Newell (2012)). The generality of a patent is defined in the following way:

$$Generality_i = 1 - \sum_{j}^{n_i} s_{ij}^2 \tag{10}$$

where s_{ij} is the percentage of patent citations *received* by patent family i that belong to patent class j (definited at 3-digit IPC code), out of n_i patent classes.[22]An originating patent with generality approaching one receives citations that are very widely dispersed across patent classes; a generality equal to zero corresponds to the case where all citations fall into a single class.

Similarly, one might suspect that clean technologies are more *original* than their dirty counterparts because they are relatively newer. We construct an originality measure using the same approach as in equation 10 but replacing s_{ij} by the percentage of citations *made* (in-

[22]Specifically, we count the number of citations made by a *patent* and receiveD by a *patent family.* This way we are only capturing citations directly made to an invention as oppose to citations made from one patent family to another.

stead of received) by invention i that belong to patent class j (defined again at 3-digit IPC code).[23]Thus, if a patent cites previous patents that belong to a narrow set of technologies the originality score will be low, whereas citing patents in a wide range of fields would render a high score.

We carry out regressions using this generality measure as a new outcome variable. Clean technologies are significantly more general and original in the transport industry while the opposite in true for the electricity production industry (see Table 12). [24] Adding generality (column 2), originality (column 3) and finally both measures (column 4) as control in Table 40 confirms the finding of greater knowledge spillovers from clean inventions. Interestingly, the coefficient is slightly smaller when adding these controls than under the baseline specification (column 1). This suggests that these measures, particularly the generality measure, explain (a small) part of the clean premium.

[23]These measures depend upon the classification system: a finer classification would render higher measures, and conversely for a coarser system. We use 3-digit IPC code as used in Hall et al. (2001)

[24]Note that there is a potential selection bias here, as patents that have never been cited have no generality measure and are therefore left out of the sample.

Table 12: Generality and Originality

	(1)	(2)	(3)	(4)	(5)	(6)
Sector	All	Transport	Electricity	All	Transport	Electricity
Dep. var.	Generality measure			Originality measure		
Clean invention	0.008*	0.047***	-0.034***	-0.003	0.049***	-0.054***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Number of patents	-0.047***	-0.081***	-0.024***	-0.050***	-0.086***	-0.027***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Family size	0.012***	0.011***	0.012***	0.008***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.001)
Triadic	0.035***	0.028***	0.046***	0.026***	0.017***	0.037***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.005)
Granted	0.047***	0.053***	0.039***	0.024***	0.024***	0.022***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	515,217	227,678	291,989	382,236	162,919	222,538

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is a generality measure (columns 1 to 3) and a originality measure (columns 4 to 6) based on Herfindahl index of concentration. The sample includes patentsin the transport sectors only (colunn 2 and 5), in the electricity sector only (column 3 and 6), and in both sectors (columns 1 and 4). All columns are estimated by OLS and include patent office-by-year-by-sector fixed effects, and month fixed effects.

4.14 Clean technologies versus other emerging fields

Technologies that contain a high degree of new knowledge (radical innovations) are likely to exhibit higher spillover effects than technologies that contain a low degree of new knowledge (incremental innovations). Clean technologies are new and rather under-developed technologies. In contrast, the dirty technologies they replace are much more mature and developed. Therefore research in clean technologies might yield spillovers that are completely different in scope from research in dirty technologies because they can be considered as radically new innovations. In order to investigate this assumption, we use several strategies.

4.14.1 Grey innovation

First, we control for the age of the invention's technological field defined as the time elapsed since the date of the first appearance of this technological field (defined at the 15-digit IPC code) in any patent. Results are reported in column 2 of Table 13. Controlling for the age of the technology decreases the coefficient obtained for the clean dummy variable. In order to account for potential non-linearities we further add squared age (column 3) and a whole range of dummy variables for each percentile of the age distribution (column 4). This exercise further diminishes the clean coefficient from 0.430 to 0.353, indicating that part of the clean premium is explained by the relative novelty of the field.

Second, we distinguish between inventions which are radically clean from those which are related to energy efficiency improvements that make the dirty technology less dirty. So far, our paper revolves mostly around a distinction between radically clean innovations (e.g. electric cars, wind turbines) and dirty innovations (e.g. combustion engines, coal power plants). In the results presented thus far we have included grey innovations in the "dirty" category. We now identify these inventions and label these "grey" innovations. In tables 14 and 23, we compare clean inventions with grey inventions (column 2), grey and truly dirty inventions

Table 13: Controlling for age of technological field

	(1)	(2)	(3)	(4)
Dep. var.	Citations received			
Clean invention	0.410***	0.381***	0.363***	0.354***
	(0.013)	(0.013)	(0.013)	(0.013)
Number of patents	-0.094***	-0.052***	-0.043***	-0.046***
	(0.004)	(0.005)	(0.005)	(0.005)
Family size	0.070***	0.067***	0.068***	0.068***
	(0.004)	(0.003)	(0.003)	(0.003)
Triadic	0.448***	0.431***	0.406***	0.397***
	(0.035)	(0.035)	(0.034)	(0.034)
Granted	0.939***	0.929***	0.917***	0.912***
	(0.031)	(0.030)	(0.030)	(0.030)
Age of tech field		-0.177***	0.194***	
		(0.009)	(0.034)	
Age of tech field^2			-0.023***	
			(0.002)	
Age of tech dummies	no	no	no	yes
Observations	1,149,237	1,149,237	1,149,237	1,149,237

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 14: Clean, Grey and True Dirty

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	Citations received			
Clean/Grey invention	0.430***	0.191***	0.307***	0.502***
	(0.014)	(0.016)	(0.016)	(0.015)
Number of patents	-0.057***	-0.051***	-0.114***	-0.060***
	(0.007)	(0.009)	(0.005)	(0.007)
Family size	0.073***	0.069***	0.072***	0.071***
	(0.004)	(0.007)	(0.004)	(0.004)
Triadic	0.456***	0.481***	0.454***	0.441***
	(0.036)	(0.055)	(0.037)	(0.035)
Granted	0.947***	0.997***	0.977***	0.868***
	(0.031)	(0.035)	(0.033)	(0.027)
Observations	1,149,988	326,942	978,179	1,006,996

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

(column 3), and finally clean with truly dirty inventions only (column 4). As a benchmark, column 1 simply reproduces the results from table6 where grey innovations are included in the dirty category. This analysis suggests a clear ranking in citations counts: clean technologies exhibit significantly higher levels of spillovers than grey technologies, which themselves outperform truly dirty technologies. From a policy perspective, this result implies that radically clean technologies should receive higher public support than incremental innovation in dirty technologies.

Third, we compare knowledge spillovers between clean inventions in the transport and electricity technologies to other radically new technologies, namely IT, biotechnologies, nanotechnologies, robots and 3D (see Table 22 for the list of related IPC codes). Results in table 15 show that clean inventions receive 41% more citations than biotech inventions. However, clean inventions receive significantly fewer citations than inventions in the IT,

Table 15: Spillovers from clean and other new technologies

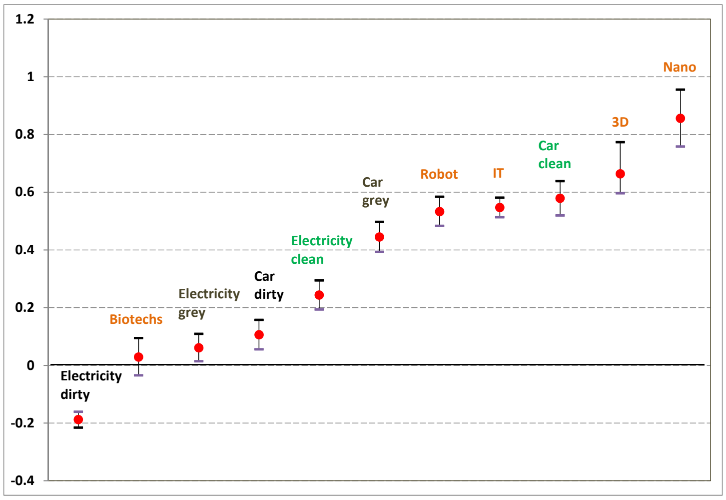
	(1)	(2)	(3)	(4)	(5)
Baseline sector	IT	Biotechs	Nano	Robot	3D
Dep. var.			Citations received		
Clean invention	-0.153***	0.408***	-0.337***	-0.127***	-0.278***
	(0.029)	(0.033)	(0.062)	(0.042)	(0.036)
Number of patents	-0.013	-0.160***	-0.031***	-0.039***	-0.037***
	(0.008)	(0.014)	(0.008)	(0.008)	(0.008)
Family size	0.020***	0.033***	0.063***	0.063***	0.062***
	(0.003)	(0.005)	(0.007)	(0.007)	(0.007)
Triadic	0.574***	0.663***	0.525***	0.550***	0.528***
	(0.057)	(0.053)	(0.070)	(0.069)	(0.068)
Granted	1.181***	0.806***	0.862***	0.877***	0.882***
	(0.065)	(0.023)	(0.038)	(0.036)	(0.037)
Observations	1,445,552	403,294	180,441	198,602	185,726

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes all clean patents (transport and electricity) and patents from the following technologies: IT (column 1), bioechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

nanotechnology, robot and 3D industries. In tables 40 and 42, we find that clean inventions are less general and less original than all new technologies apart from nanotechnologies. Taken together, these results suggest that the relative novelty of clean technologies might explain why they exhibit larger spillovers. Looking at the coefficients obtained for the clean invention variable, it is interesting to note that knowledge spillovers from clean technologies appear comparable to those in the IT sector, which has been behind the third industrial revolution.

Fourth, we compare the previous sample (clean transport, clean electricity, IT, biotech, nano, robots and 3D) to all other inventions. Figure 5 plots the coefficient of the dirty (in black), grey (in grey), clean (in green) and radically new technologies (in orange). Clean transport and electricity exhibit larger spillovers than the average invention. In terms of relative ranking, the clean transport and clean electricity are positioned between their dirty

Figure 5: Clean, grey, dirty, and radically new technologies vs. all other technologies-Citations count



counterparts and radically new technologies.

Fifth, we restrict the sample of radically new technologies (IT, biotechs, nano, and robots) and compare clean and dirty inventions within these technologies. While clean inventions within the IT and the biotechs technologies still exhibit larger knowledge spillovers, there is no clean advantage within the nano and robot sectors.

Finally, in an attempt to find a dirty yet radically new technology, we compare knowledge spillovers between clean electricity production technologies and carbon capture and storage technologies (CCS) in table 17. The clean advantage disappears when considering simple patent counts and PatentRank, suggesting it is not because they are clean that clean technologies generate larger knowledge spillovers.

Table 16: Comparing spillovers from clean and dirty within new technologies

	(1)	(2)	(3)	(4)
Sector	IT	Biotechs	Nano	Robot
Dep. var.	Citations received			
Clean invention	0.222*	0.609**	0.313	0.677
	(0.091)	(0.053)	(0.211)	(0.525)
Number of patents	-0.012	-0.257***	-0.169***	-0.051
	(0.008)	(0.016)	(0.044)	(0.047)
Family size	0.020***	0.033***	0.109***	0.104***
	(0.003)	(0.005)	(0.018)	(0.014)
Triadic	0.547***	0.583***	0.268*	0.387***
	(0.055)	(0.056)	(0.136)	(0.113)
Granted	1.220***	0.699***	0.961***	1.005***
	(0.072)	(0.031)	(0.145)	(0.053)
Observations	1,270,842	227,100	1,481	22,266

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes patents from the following technologies: IT (column 1), bioechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 17: Spillovers from clean and CCS technologies

Dep. var.	Citations received
Clean invention	-0.083*
	(0.034)
Number of patents	0.037***
	(0.010)
Family size	0.065***
	(0.006)
Triadic	0.477***
	(0.062)
Granted	0.681***
	(0.030)
Observations	106,700

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes clean electricity production inventions and CO2 Capture and Storage technology. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

5 Monetary value of knowledge spillovers

5.1 Market value equation

In order to quantify the economic value of knowledge spillovers, in particular clean knowledge spillovers, we estimate a market valuation equation using firm-level data. Following Hall et al. (2005), a firm's knowledge assets are modeled as being accumulated in a continuously ongoing innovative process in which R&D expenditures reflect innovative input, patents record the successful innovations that can be appropriated by the firm, and citations received by the firm's patents (forward citations) measure the relative importance of the patents. We also include citations made (backward citations) as in Deng (2008) as a proxy of the knowledge flows the firm has received, which are considered an additional kind of innovative input to direct R&D spendings on the belief that more knowledge inflows increase the firm's knowledge stock and may boost the firm's R&D productivity. We extend Deng (2008)'s analysis by further distinguishing between clean and dirty backward citations to capture knowledge spillovers from clean and dirty technologies.

Consider Griliches (1981)'s market valuation equation

$$V_{it} = q_t(A_{it} + \beta K_{it} + \gamma R_{it} + \eta S_{it}) \tag{11}$$

where V_{it} denotes firm i's stock market value in year t, A_{it} the book value of its physical assets, and K_{it} the knowledge assets. q_t represents the shadow value of firms' assets, and the coefficient b measures the shadow value of knowledge assets relative to physical assets. σ measures the scale effects in the value function and is assumed to be one.

Taking the logarithm, we have the following estimation equation:

$$\log Q_{it} = \log(\frac{V_{it}}{A_{it}}) = \log q_t + \log(1 + \beta\frac{K_{it}}{A_{it}}) + \varepsilon_{it} \tag{12}$$

where Q_{it} represents Tobin's q and ε_{it} are the prediction errors.

As Deng (2008), we use the following value function to evaluate the firm's knowledge assets

$$K_{it} = f(R\&D_{it}, BCIT_{it}, \omega_{it}) \tag{13}$$

where $R\&D_{it}$denotes the accumulated R&D spendings, $BCIT_{it}$ the accumulated backward citations the firm has made as a proxy of the knowledge inflows received by the firm, and ω_{it} the accumulated idiosyncratic productivity shocks in the firm's inventive activities. ω_{it} is proxied by the patent / R&D ratio, weighted by the average number of forward citations the firm's patents receive over their entire lives (Hall et al. (2005)). This can be viewed as the knowledge outflow made by the firm.

Taking first-order Taylor expansion of equation 5 yields

$$K_{it} = f_1 \times R\&D_{it} + f_2 \times BCIT_{it} + f_3 \times \frac{PAT_{it}}{R\&D_{it}} + f_4 \times \frac{FCIT_{it}}{PAT_{it}} \tag{14}$$

where PAT_{it} and $FCIT_{it}$ are firm i's patent stock and forward citations stock in year t respectively. Combining equations 5 and 6 leads to

$$\log Q_{it} = \log q_t + \log(1 + \beta_1 \frac{R\&D_{it}}{A_{it}} + \beta_2 \frac{BCIT_{it}}{PAT_{it}} + \beta_3 \frac{PAT_{it}}{R\&D_{it}} + \beta_4 \frac{FCIT_{it}}{PAT_{it}}) + \varepsilon_{it} \tag{15}$$

The coefficient β_2 represents the value of knowledge flows brought by an additional backward citation, and $\frac{\beta_2}{\beta_1}$ is a direct measure of the monetary value of knowledge spillovers in terms of R&D equivalent dollar.

We will estimate equation (9) using a non-linear least square including a full set of year and NACE dummies or firm fixed effects.

5.2 Firm level data

For this purpose, we combine the PATSTAT database with the ORBIS database which contains firm-level information such as R&D expenses, market value, and total number of assets. The analysis focuses on 10,299 firms from 2001 to 2011 for which we can match both datasets and identify each firm's patents along with the citations (both backward and forward) associated to them.

We calculate the stock of R&D (patents) as the accumulated past R&D expenditures (the number of patents) subject to an annual deprecitation rate assumed to be a constant 10%. As previously we measure patents and their citations at the patent family level. The stock of backward citations is measured taking into account the age of the patent and then aggregate them over the firm's patent portfolio each year subject to the annual depreciation of 15%. We remove self-citations among these backward citations. The stock of forward citations measures the relative importance of a firm's portfolio. Given the truncation issues associated to the tine lag in observing forward citations, we limit our sample up to 2011 and scale citations taking into account the average citations across publication years, patent offices, sector and citation year. We finally aggregate these scaled forward citations subject to annual depreciation. A table of descriptive statistics can be found in table 18.

5.3 Estimating the market value of clean knowledge spillover

Table 19 shows a significant positive monetary value for knowledge spillovers. The first three columns include a full set of year and NACE dummies, while the last three columns incorporate firm fixed effects. The coefficient estimates of R&D/assets and forward citations/patents are positive and significant. A one-percentage point increase in R&D/assets ratio leads to a 0.4% appreciation in the firm value. A rise in the average quality of the firm's patent portfolio also raises the firm's market value – if every patent receives one more

Table 18: Descriptive Statistics, 2001-2008, N = 29,154

	Mean	Median	Min	Max	Std. Dev.
Market Value ($M)	2.860	0.208	0.001	512	13.9
Total assets ($M)	3.526	0.319	0.00007	798	17.5
Tobin's Q	1.148	0.695	0.045	15.517	1.476
Profits/Losses ($M)	0.358	0.027	0	83.4	1.852
Operating revenue ($M)	2.862	0.285	0	460	12.3
Number of employees	8424.873	1266	1	550000	28321.2
R&D stock ($M)	0.191	0.005	0	37.5	1.225
R&D stock ($M) for 20,745 obs. with R&D>0	0.266	0.017	1	37.5	1.439
D(R&D) = 0	0.282	0	0	1	0.450
Patent stock	254.033	4.892	0	88013.93	2252.876
R&D stock / Total assets	0.1585	0.021	0	209.654	1.459
Patent stock / R&D stock	0.014	0.001	0	34.163	0.355
Fwd citation stock / Patent stock	4.428	2.149	0	222	7.668
Bwd citation stock / Patent stock	2.928	1.635	0	77.004	4.133
Clean bwd citation stock / Patent stock	0.038	0	0	11.746	0.316
Dirty bwd citation stock / Patent stock	0.059	0	0	8.299	0.316
Other bwd citation stock / Patent stock	2.831	1.538	0	76.482	4.099

forward citation over their entire lives, the firm's value will rise between 0.07% and 0.1%. Adding knowledge spillovers means that one extra backward citation per patent makes the firm about 0.07% more valuable. The amount of appreciation is no longer significant once we control for firm fixed effects. Columns 3 and 6 distinguishes among the type of spillovers. We see that knowledge spillovers from clean and other technologies are positive although less significant when including firm fixed effects. Of particular interest is the monetary value of clean spillovers. One extra clean backward citation per patent makes the firm about 0.13% more valuable, and the amount of appreciation is even larger to 0.15% when we include firm fixed effects. Given the fact that patents recive on average of 2.899 citations in our sample, our results translate to an average

We conduct a number of robustness checks. First,we investigate our results by sector (NACE codes) and firm country. We find that our results are mainly driven by firms in the manufacturing industry and in the United States (see table 50). Second, we add a number of

Table 19: Estimation of Tobin's Q equation

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			ln Tobin's Q			
ln (R&D/assets)	0.441***	0.431***	0.432***	0.144***	0.145***	0.145***
	(0.029)	(0.029)	(0.029)	(0.037)	(0.037)	(0.037)
ln (Patent/R&D)	0.020	0.040	0.040	-0.030	-0.027	-0.027
	(0.043)	(0.045)	(0.045)	(0.023)	(0.024)	(0.024)
ln (Fwd citations/patent)	0.101***	0.048***	0.047***	0.076***	0.064***	0.064***
	(0.006)	(0.009)	(0.009)	(0.013)	(0.014)	(0.014)
ln (Bwd cites/patent)		0.078***			0.030**	
		(0.010)			(0.014)	
ln (Bwd clean cites/ patent)			0.118***			0.149**
			(0.039)			(0.066)
ln (Bwd dirty cites/ patent)			0.050			0.038
			(0.034)			(0.042)
ln (Bwd other cites/ patent)			0.074***			0.009
			(0.010)			(0.014)
D(R&D=0)	0.080***	0.080***	0.080***	0.007	0.007	0.013
	(0.011)	(0.011)	(0.011)	(0.015)	(0.015)	(0.015)
Year + NACE	Yes	Yes	Yes	No	No	No
Firm FE	No	No	No	Yes	Yes	Yes
Observations	23,654	23,654	23,654	23,659	23,659	23,659

Notes: Clustered standard errors in parentheses (* p<0.1, ** p<0.05, *** p<0.01). The dependent variable is the ln Tobin's Q defined as the stock market value over the book value of physical assets. We restrict the sample to patents applied for between 2000 and 2008. All columns are estimated by OLS. Columns 1, 2, and 3 include a complete set of year and NACE dummies while columns 4, 5, and 6 include firm fixed effects.

variables to control for the quality of the patents. We use the average characteristics such as the family size, generality and originality of cited patents, and the PatentRank of the patents held by the firm each year (see table 51). Third, we base our patent and citation counts on granted patents only. Patent counts may suffer from biases due to truncation because only a fraction of patents are eventually granted and, if they are granted, there is a lag between application and granted dates (see table 52). All these robustness checks confirm the conclusion found in the main table of results.

6 Discussion and conclusion

In this paper we compare the relative intensity of knowledge spillovers from clean and dirty technologies. To measure knowledge spillovers, we use a rich dataset of 3 million citations received by over a million inventions patented in the automobile and electricity production sectors. This analysis is crucial to answer the question of whether clean technologies warrant higher subsidies than dirty ones. Our results unambiguously show that clean technologies induce larger knowledge spillovers than their dirty counterparts. Moreover, we provide a measure of the economic values of knowledge externalities of relevant clean technologies. We find that evidence of larger monetary value associated to knowledge spillovers from clean technology. We conduct a large number of sensitivity tests and the findings are remarkably robust. In particular, as depicted by the innovation flowers, this result is confirmed when using a completely novel methodology to measure knowledge spillovers that does not only count immediate forward citations but takes into account the whole network of patent citations.

We explore five potential explanations for our findings. First, we find no evidence that the clean industry is more geographically clustered. Second, differential citations behaviors among scientists involved in clean technologies cannot fully explain the clean advantage. Third, we find no evidence that government spending cannot account for clean premium. Fourth, we examine the generality and originality features of clean inventions. We find that clean inventions in the automobile industry are more general (i.e. they are cited by a wider range of technological fields) and more original. However, clean inventions in the electricity production industry are less general and less original. Finally, we compare clean inventions to other radically new inventions such as IT, biotechnologies and nanotechnologies. We conclude that clean inventions seem to benefit from early returns to scale and steep learning curves. Interestingly we observe that knowledge spillovers from clean technologies appear comparable in scope to those in the IT sector.

Our results have two important policy implications. Firstly, the larger knowledge spillovers from clean technologies uncovered in this study justify higher subsidies for clean R&D or specific R&D programs for clean technologies, in addition to implicit support for clean R&D trough climate policies such as carbon taxation. Radically new clean technologies should receive higher public support than research activities targeted at improving on the existing dirty technologies.[25] However, such specific support could equally be justified for a range of other emerging areas, such as nanotechnologies or IT. This recommendation has been made in the past, for instance by Hart (2008) or Acemoglu et al. (2012) but it is the first time to our knowledge that it is substantiated by robust empirical evidence.[26]While a first best policy scenario would suggest a combination of emissions pricing and R&D subsidies *specifically* targeted at clean technologies, in times of tight government budgets it might be difficult to achieve the necessary subsidy levels. There might also be concerns over governments' ability to channel funds to R&D projects with the highest potential either because of information asymmetry or because of political interference. In this case our results would support a second best policy with more stringent emission pricing and regulation that would otherwise be the case (see for example Gerlagh et al. (2009); Hart (2008); Kverndokk et al. (2004); Kverndokk and Rosendahl (2007)).

Secondly, our results lend support to the idea that a redirection of innovation from dirty to clean technologies induced by environmental or climate policies can lead to higher growth

[25]Importantly, our results suggest that the relative support to clean R&D should grow over time. Incidentally, in a recent working paper Daubanes et al. (2013) show that gradual rise in subsidies to clean R&D activities causes a less rapid extraction of fossil resources, because it enhances the long-run resource productivity.

[26]Interestingly, statistics in OECD countries show that there is higher public R&D spending in clean technologies than in dirty ones. A look at the International Energy Agency's R&D expenditures data reveals that between 2000 and 2012, OECD countries have spent 198 million euros on dirty cars and 18 billion euros on dirty energy but 327 million euros on clean cars (65% more than dirty cars) and 25 billion euros on clean energy (35% more than dirty energy). However, these numbers do not include subsidies to *private* clean R&D, which is also warranted in a first best policy setting.

in the short and medium run. This can happen if the larger spillover effects from clean technologies exceed any negative growth effects from more stringent regulation. Our results however suggest that the potential growth effects of environmental policies very much depend on the type of displacement being induced by increasing support for clean technologies. If clean innovation crowds out dirty innovation, as shown by Aghion et al. (2012) for the transport industry, there is scope for medium run growth effects. If innovation in other emerging areas is crowded out, such effects are less likely. At any rate, one should keep in mind that higher spillovers are only a necessary but not a sufficient condition for growth effects from green policies.

Our work can be extended in several directions. First, it would be interesting to investigate how knowledge spillovers affect firms' decisions to invest in radical innovation (clean technologies) or in incremental innovation (less dirty technologies), and how they respond to R&D subsidies targeted at clean technologies. Second, an interesting direction is to understand the spatial pattern of knowledge diffusion for clean technologies, including the transfer of knowledge across borders, in particular between developed and developing countries. Third, we could use micro data to estimate the impact of knowledge spillovers from clean and dirty technologies on firms' productivity. These parameters are crucial to empirically validate the potential impact of green policies on economic growth.

Radically new clean innovations that require consumers to substitute to a different product (e.g. electric vehicles replacing internal combustion engine propelled vehicles) or more incremental innovations that improve the energy efficiency of current (dirty) products (for example fuel efficiency technologies for combustion engines). We label this latter category as "grey" inventions. From a policy point of view an important question is whether to give priority to clean or grey innovation in order to mitigate climate change (see Aghion et al. (2012), for a further discussion on this issue).

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1):131–66.

Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., and Van Reenen, J. (2012). Carbon taxes, path dependency and directed technical change: Evidence from the auto industry. NBER Working Papers 18596, National Bureau of Economic Research, Inc.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60 (2):323–351.

Aghion, P. and Howitt, P. (1996). Research and development in the growth process. *Journal of Economic Growth*, 1(1):49–73.

Aghion, P. and Howitt, P. (1998). *Endogenous growth theory*. MIT press.

Alcacer, J. and Gittelman, M. (2006). Patent citations as a measure of knowledge flows: The influence of examiner citations. *The Review of Economics and Statistics*, 88(4):774–779.

Alcacer, J., Gittelman, M., and Sampat, B. (2009). Applicant and examiner citations in us patents: An overview and analysis. *Research Policy*, 38(2):415–427.

Allison, J. R., Lemley, M. A., Moore, K. A., and Trunkey, R. D. (2003). Valuable patents. *Geo. Lj*, 92:435.

Allison, P. D. and Waterman, R. P. (2002). Fixed–effects negative binomial regression models. *Sociological methodology*, 32(1):247–265.

Ambec, S. and Barla, P. (2006). Can environmental regulations be good for business? an assessment of the porter hypothesis. *Energy studies review*, 14(2):1.

Ambec, S., Cohen, M. A., Elgie, S., and Lanoie, P. (2013). The porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy*, 7(1):2–22.

Audretsch, D. and Feldman, M. (2004). Knowledge spillovers and the geography of innovation. *Handbook of regional and urban economics*, 4:2713–2739.

Bjørner, T. B. and Mackenhauer, J. (2013). Spillover from private energy research. *Resource and Energy Economics*.

Braun, F., Schmidt-Ehmcke, J., and Zloczysti, P. (2010). Innovative activity in wind and solar technology: Empirical evidence on knowledge spillovers using patent data.

Breschi, S. and Lissoni, F. (2005). Knowledge networks from patent data. In *Handbook of quantitative science and technology research*, pages 613–643. Springer.

Bresnahan, T. F. and Trajtenberg, M. (1995). General purpose technologies 'engines of growth'? *Journal of econometrics*, 65(1):83–108.

Caballero, R. and Jaffe, A. (1993). How high are the giants' shoulders: An empirical assessment of knowledge spillovers and creative destruction in a model of economic growth. In *NBER Macroeconomics Annual 1993, Volume 8*, pages 15–86. MIT press.

Case, D. O. and Higgins, G. M. (2000). How can we investigate citation behavior? a study of reasons for citing literature in communication. *Journal of the American Society for Information Science*, 51(7):635–645.

Chernozhukov, V., Fernández-Val, I., and Melly, B. (2013). Inference on counterfactual distributions. *Econometrica*, 81(6):2205–2268.

Cockburn, I., Kortum, S., and Stern, S. (2003). Are all patent examiners equal? examiners, patent characteristics, and litigation outcomes. *Patents in the knowledge-based economy*, 35.

Collins, P. and Wyatt, S. (1988). Citations in patents to the basic research literature. *Research Policy*, 17(2):65–74.

Criscuolo, P. (2006). The'home advantage'effect and patent families. a comparison of oecd triadic patents, the uspto and the epo. *Scientometrics*, 66(1):23–41.

Daubanes, J., Grimaud, A., and Rougé, L. (2013). Green paradox and directed technical change: The effects of subsidies to clean R&D. Technical report, Institut d'Économie Industrielle (IDEI), Toulouse.

Deng, Y. (2008). The value of knowledge spillovers in the us semiconductor industry. *International Journal of Industrial Organization*, 26(4):1044–1058.

Dernis, H. and Khan, M. (2004). Triadic patent families methodology. Technical report, OECD Publishing.

Fischer, C. and Newell, R. (2008). Environmental and technology policies for climate mitigation. *Journal of environmental economics and management*, 55(2):142–162.

Fischer, C., Newell, R., and Preonas, L. (2013). Environmental and technology policy options in the electricity sector: Interactions and outcomes. *Working paper.*

Gerlagh, R., Kverndokk, S., and Rosendahl, K. E. (2009). Optimal timing of climate change policy: Interaction between carbon taxes and innovation externalities. *Environmental and resource Economics*, 43(3):369–390.

Goulder, L. H. and Schneider, S. H. (1999). Induced technological change and the attractiveness of co2 abatement policies. *Resource and Energy Economics*, 21(3):211–253.

Greaker, M. and Heggedal, T.-R. (2012). A comment on the environment and directed technical change. Technical report.

Greene, W. H. (2007). Fixed and random effects models for count data. *Working paper, Department of Economics, Stern School of Business, New York University, New York*.

Griliches, Z. (1981). Market value,< i> r&d</i>, and patents. *Economics letters*, 7(2):183–187.

Griliches, Z. (1992). The search for R&D spillovers. Technical report, National Bureau of Economic Research.

Griliches, Z., Hall, B. H., and Pakes, A. (1991). R&D, patents, and market value revisited: is there a second (technological opportunity) factor? *Economics of Innovation and new technology*, 1(3):183–201.

Grossman, G. and Helpman, E. (1991). Innovation and growth in the world economy.

Grupp, H. (1998). *Foundations of the economics of innovation: theory, measurement, and practice*. E. Elgar.

Grupp, H., Münt, G., and Schmoch, U. (1996). Assessing different types of patent data for describing high-technology export performance. *Innovation, patents and technological strategies*, pages 271–287.

Guellec, D. and Van Pottelsberghe de la Potterie, B. (2004). From R&D to productivity growth: Do the institutional settings and the source of funds of R&D matter? *Oxford Bulletin of Economics and Statistics*, 66(3):353–378.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2001). The nber patent citation data file: Lessons, insights and methodological tools. Technical report, National Bureau of Economic Research.

Hall, B. H., Jaffe, A. B., and Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of economics*, pages 16–38.

Harhoff, D., Scherer, F. M., and Vopel, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, 32(8):1343–1363.

Hart, R. (2004). Growth, environment and innovation - a model with production vintages and environmentally oriented research. *Journal of Environmental Economics and Management*, 48(3):1078–1098.

Hart, R. (2007). Can environmental regulations boost growth? In *Sustainable Resource Use and Economic Dynamics*, pages 53–70. Springer.

Hart, R. (2008). The timing and balance of policies for CO_2 abatement when technological change is endogenous. *Journal of Environmental Economics and Management*, 55:194–212.

Hausman, J., Hall, B. H., and Griliches, Z. (1984). Econometric models for count data with an application to the patents- R&D relationship. *Econometrica*, 52(4):909–38.

Hegde, D. and Sampat, B. (2009). Examiner citations, applicant citations, and the private value of patents. *Economics Letters*, 105(3):287–289.

Henderson, R., Jaffe, A. B., and Trajtenberg, M. (1998). Universities as a source of commercial technology: a detailed analysis of university patenting, 1965–1988. *Review of Economics and Statistics*, 80(1):119–127.

Jaffe, A. B., Newell, R. G., and Stavins, R. (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics*, 54(2):164–174.

Jaffe, A. B. and Trajtenberg, M. (1996). Flows of knowledge from universities and federal labs: Modeling the flowof patent citations over time and across institutional and geographic boundari. NBER Working Papers 5712, National Bureau of Economic Research, Inc.

Jaffe, A. B. and Trajtenberg, M. (1999). International knowledge flows: Evidence from patent citations. *Economics of Innovation and New Technology*, 8(1-2):105–136.

Jaffe, A. B., Trajtenberg, M., and Fogarty, M. S. (2000). Knowledge spillovers and patent citations: Evidence from a survey of inventors. *NBER/Sloan˜*, page 21.

Jaffe, A. B., Trajtenberg, M., and Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics*, 108(3):577–598.

Jones, C. I. (2005). Growth and ideas. *Handbook of Economic Growth*, 1:1063–1111.

Keller, W. (2004). International technology diffusion. *Journal of Economic Literature*, 42(3):752–782.

Kverndokk, S. and Rosendahl, K. E. (2007). Climate policies and learning by doing: Impacts and timing of technology subsidies. *Resource and Energy Economics*, 29(1):58–82.

Kverndokk, S., Rosendahl, K. E., and Rutherford, T. F. (2004). Climate policies and induced technological change: Which to choose, the carrot or the stick? *Environmental and Resource Economics*, 27(1):21–41.

Lanjouw, J. and Mody, A. (1996). Innovation and the international diffusion of environmentally responsive technology. *Research Policy*, 25(4):549–571.

Lanjouw, J. O. and Schankerman, M. (1999). The quality of ideas: measuring innovation with multiple indicators. Technical report, National Bureau of Economic Research.

Lanjouw, J. O. and Schankerman, M. (2004). Patent quality and research productivity: Measuring innovation with multiple indicators. *The Economic Journal*, 114(495):441–465.

Leopold, A. (1973). Games scientists play. *BioScience*, 23(10):590–594.

Lukach, R. and Lukach, M. (2007). Ranking USPTO patent documents by importance using random surfer method (pagerank). *Available at SSRN 996595*.

Maslov, S. and Redner, S. (2009). Promise and pitfalls of extending google's pagerank algorithm to citation networks. *Mimeo, Division of Material Science, U.S. Department of Energy*.

Maurseth, P. and Verspagen, B. (2002). Knowledge spillovers in europe: a patent citations analysis. *The Scandinavian journal of economics*, 104(4):531–545.

Merton, R. K. (1957). Priorities in scientific discovery: a chapter in the sociology of science. *American sociological review*, pages 635–659.

Michel, J. and Bettels, B. (2001). Patent citation analysis. a closer look at the basic input data from patent search reports. *Scientometrics*, 51(1):185–201.

Mohr, R. D. (2002). Technical change, external economies, and the porter hypothesis. *Journal of Environmental economics and management*, 43(1):158–168.

Neuhoff, K. (2005). Large-scale deployment of renewables for electricity generation. *Oxford Review of Economic Policy*, 21(1):88–110.

Noailly, J., Shestalova, V., et al. (2013). Knowledge spillovers from renewable energy technologies lessons from patent citations. Technical report, CPB Netherlands Bureau for Economic Policy Analysis.

Otto, V. M., Löschel, A., and Dellink, R. (2007). Energy biased technical change: a cge analysis. *Resource and Energy Economics*, 29(2):137–158.

Otto, V. M., Löschel, A., and Reilly, J. (2008). Directed technical change and differentiation of climate policy. *Energy Economics*, 30(6):2855–2878.

Packalen, M. and Bhattacharya, J. (2012). Words in patents: Research inputs and the value of innovativeness in invention. Technical report, National Bureau of Economic Research.

Page, L., Brin, S., Motwani, R., and Winograd, T. (1999). The pagerank citation ranking: bringing order to the web.

Peri, G. (2005). Determinants of knowledge flows and their effect on innovation. *Review of Economics and Statistics*, 87(2):308–322.

Popp, D. and Newell, R. (2012). Where does energy R&D come from? examining crowding out from energy R&D. *Energy Economics*, 34(4):980–991.

Popp, D., Newell, R., and Jaffe, A. (2009). Energy, the environment, and technological change. NBER Working Papers 14832, National Bureau of Economic Research, Inc.

Porter, M. E. and Van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *The journal of economic perspectives*, 9(4):97–118.

Ricci, F. (2007a). Channels of transmission of environmental policy to economic growth: A survey of the theory. *Ecological Economics*, 60(4):688–699.

Ricci, F. (2007b). Environmental policy and growth when inputs are differentiated in pollution intensity. *Environmental and Resource Economics*, 38(3):285–310.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, pages S71–S102.

Sampat, B. (2005). Determinants of patent quality: an empirical analysis. *Columbia Univ., New York*.

Scherer, F. M. (1965). Firm size, market structure, opportunity, and the output of patented inventions. *The American Economic Review*, 55(5):1097–1125.

Schmoch, U. (1993). Tracing the knowledge transfer from science to technology as reflected in patent indicators. *Scientometrics*, 26(1):193–211.

Schmookler, J. (1966). *Invention and economic growth*, volume 26. Harvard University Press Cambridge, MA.

Schneider, S. H. and Goulder, L. H. (1997). Achieving low-cost emissions targets. *Nature*, 389(6646):13–14.

Shaffer, M. J. (2011). *Entrepreneurial Innovation: Patent Rank and Marketing Science*. PhD thesis, Washington State University.

Silva, J. S. and Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4):641–658.

Silverman, A. (2003a). Duty to disclose prior art to the united states patent and trademark office. *JOM*, 55:64–64.

Silverman, A. B. (2003b). Duty to disclose prior art to the united states patent and trademark office. *JOM Journal of the Minerals, Metals and Materials Society*, 55(10):64–64.

Small, H. and Griffith, B. C. (1974). The structure of scientific literatures i: Identifying and graphing specialties. *Science studies*, pages 17–40.

Smulders, S. and De Nooij, M. (2003). The impact of energy conservation on technology and economic growth. *Resource and Energy Economics*, 25(1):59–79.

Smulders, S. and Withagen, C. (2012). Green growth–lessons from growth theory. *World Bank Policy Research Working Paper*, (6230).

Stuart, T. E. and Podolny, J. M. (1996). Local search and the evolution of technological capabilities. *Strategic Management Journal*, 17(S1):21–38.

Thompson, P. and Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, pages 450–460.

Trajtenberg, M. (1990). A penny for your quotes: patent citations and the value of innovations. *The Rand Journal of Economics*, pages 172–187.

Trajtenberg, M., Henderson, R., and Jaffe, A. (1997). University versus corporate patents: A window on the basicness of invention. *Economics of Innovation and New Technology*, 5(1):19–50.

Van Pottelsberghe, B., Denis, H., and Guellec, D. (2001). Using patent counts for cross-country comparisons of technology output. Technical report, ULB–Universite Libre de Bruxelles.

Veefkind, V., Hurtado-Albir, J., Angelucci, S., Karachalios, K., and Thumm, N. (2012). A new EPO classification scheme for climate change mitigation technologies. *World Patent Information*, 34(2):106–111.

Verdolini, E. and Galeotti, M. (2011). At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. *Journal of Environmental Economics and Management*, 61(2):119–134.

Appendix

Table 20: Patent classification codes - Transport

CLEAN	
B60K 1	Arrangement or mounting of electrical propulsion units
B60K 6	Arrangement or mounting of hybrid propulsion systems comprising electric motors and internal combustion
B60L 3	Electric devices on electrically-propelled vehicles for safety purposes: Monitoring operating variables e.g. speed, deceleration, power consumption
B60L 7	Dynamic electric regenerative braking
B60L 11	Electric propulsion with power supplied within the vehicle
B60L 15	Methods, circuits, or devices for controlling the traction-motor speed of electrically-propelled vehicles
B60R 16	Electric or fluid circuits specially adapted for vehicles and not otherwise provided for
B60S 5	Supplying batteries to, or removing batteries form
B60W 10	Conjoint control of vehicles sub-units of different type or different function
B60W 20	Control systems specially adapted for hybrid vehicles
H01M	Fuel cells
GREY	
F02M 39/71	Fuel injection apparatus
F02M 3/02-05	Idling devices for carburettors preventing flow of idling fue
F02M 23	Apparatus for adding secondary air to fuel-air mixture
F02M 25	Engine-pertinent apparatus for adding non-fuel substances or small quantities of secondary fuel to combustion-air, main fuel, or fuel-air mixture
F02D 41	Electric control of supply of combustion mixture or its constituents
F02B 47/06	Methods of operating engines involving adding non-fuel substances or anti-knock agents to combustion air, fule, or fuel-air mixtures of engines, the substances including non-airborne oxygen
DIRTY	
F02B	Internal-combustion piston engines; combustion engines in genera
F02D	Controlling combustion engines
F02F	Cylinders, pistons, or casings for combustion engines; arragement of sealings in combustion engines
F02M	Supplying combustion engines with combustiles mixtures or constituents thereof
F02N	Starting of combustion engines
F02P	Ignition (other than compression ignition) for internal-combustion engines

Table 21: Patent classification codes - Electricity Production

CLEAN	
Y02E10	Energy generation through renewable energy sources
Y02E30	Energy generation of nuclear origin
E02B9/08	Tide or wave power plants
F03B13/10-26	Submerged units incorporating electric generators or motors characterized by using wave or tide energy
F03D	Wind motors
F03G4	Devices for producing mechanical power from geothermal energy
F03G6	Devices for producing mechanical power from solar energy
F03G7/05	Ocean thermal energy conversion
F24J2	Use of solar heat, e.g. solar heat collectors
F24J3/08	Production or use of heat, not derived from combustion using geothermal heat
F26B3/28	Drying solid materials or objects by processes involving the application of heat by radiation, e.g. from the sun
GREY	
Y02E50	Technologies for the production of fuel of non-fossil origin
Y02E20/10	Combined combustion
Y02E20/12	Heat utilisation in combustion or incineration of waste
Y02E20/14	Combined heat and power generation
Y02E20/16	Combined cycle power plant, or combined cycle gas turbine
Y02E20/18	Integrated gasification combined cycle
Y02E20/30	Technologies for a more efficient combustion or heat usage
Y02E20/32	Direct C02 mitigation
Y02E20/34	Indirect C02 mitigation, by acting on non C02 directly related matters of the process, more efficient use of fuels
Y02E20/36	Heat recovery other than air pre-heating
DIRTY	
C10G1	Production of liquid hydrocarbon mixtures from oil-shale, oil-sand, or non-melting solid carbonaceous or similar materials, e.g. wood, coal, oil-sand, or the like B03B
C10L1	Fuel
C10J	Production of fuel gases by carburetting air or other gases
E02B	Hydraulic engineering
F01K	Steam engine plans; steam accumulators; engine plants not otherwise provided for; engines using special working fluids or cycles
F02C	Gas-turbine plants; air intakes for jet-propulsion plants; controlling fuel supply in air-breathing jet-propulsion plants
F22	Steam generation
F23	Combustion apparatus; combustion processes
F24J	Production or use of heat not otherwise provided for
F27	Furnaces; kilns; ovens; retorts
F28	Heat exchange in general

Table 22: Patent classification codes - Radically New Technologies

	3D
H04N 13	Stereoscopic television systems
	IT
G06	Computing; Calculating; Counting
G10L	Speech Analysis or Synthesis; Speech Recognition; Speech or Voice Processing; Speech or Audio Coding or
G11C	Static Stores
(not G06Q)	Data Processing Systems or Methods; Specially Adapted for Administrative, Commercial, Financial, Managerial, Supervisory or Forecasting purposes; Systems or Methods Specially Adapted for Administrative Commercial, Financial, Managerial, Supervisory or Forecasting purposes, not otherwise provided for
	Biotechs
C07G	Compounds of unknown constitution
C07K	Peptides
C12M	Apparatus for Enzymology or Microbiology
C12N	Micro-organisms or enzymes; compositions thereof
C12P	Fermentation or Enzyme-using Processes to Synthesise a desired chemical compound or composition or to separate optical isomers from a racemic mixture
C12Q	Measuring or Testing Processes Involving Enzymes or Micro-Organisms; Compositions or test papers therefor; Processes of preparing such compositions; Condition responsive control in microbiological or enzymological processes
C12R	Processes using micro-organisms
(not A61K)	Preparations for Medical, Dental, or Toilet Purposes
	Nano
B82	Nano-technology
	Robot
B25J 9	Programme-controlled manipulators

Patent examples

Figure 6: Patent example

US006026921A

United States Patent [19]

Aoyama et al.

[11] **Patent Number:** **6,026,921**

[45] **Date of Patent:** **Feb. 22, 2000**

[54] **HYBRID VEHICLE EMPLOYING PARALLEL HYBRID SYSTEM, USING BOTH INTERNAL COMBUSTION ENGINE AND ELECTRIC MOTOR FOR PROPULSION**

[75] Inventors: **Shunichi Aoyama**, Kanagawa; **Shinichiro Kitada**, Tokyo; **Noboru Hattori**, Kanagawa; **Isaya Matsuo**, Tokyo, all of Japan

[73] Assignee: **Nissan Motor Co., Ltd**, Yokohama, Japan

[21] Appl. No.: **09/271,326**

[22] Filed: **Mar. 18, 1999**

[30] **Foreign Application Priority Data**

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[51] **Int. Cl.**^{7} **B60K 6/02**

[52] **U.S. Cl.** **180/65.2**; 123/348; 180/65.4; 180/65.8; 701/22

[58] **Field of Search** 701/22, 105, 113; 318/8; 123/347, 348; 180/65.1, 65.2, 65.3, 65.4, 65.8

[56] **References Cited**

U.S. PATENT DOCUMENTS

4,335,429	6/1982	Kawakatsu	701/22 X
5,624,347	4/1997	Yang	180/65.2 X
5,697,466	12/1997	Moroto et al.	701/22 X
5,823,280	10/1998	Lateur et al.	180/65.2
5,823,282	10/1998	Yamaguchi	180/65.2
5,826,671	10/1998	Nakae et al.	180/65.2
5,845,731	12/1998	Buglione et al.	180/65.2
5,865,263	2/1999	Yamaguchi et al.	180/65.2

FOREIGN PATENT DOCUMENTS

5-50865 3/1993 Japan .

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Attorney, Agent, or Firm—Foley & Lardner

[57] **ABSTRACT**

A hybrid vehicle employing a parallel hybrid system, using both an internal combustion engine and an electric motor for propulsion, comprises a propulsion mechanism having at least a first electric motor, an internal combustion engine, a clutch, a second electric motor, a transmission, and drive wheels, and constructed so that a crankshaft of the engine and a motor shaft of the first electric motor are connected to an input shaft of the clutch, and that a motor shaft of the second electric motor and an input shaft of the transmission are connected to an output shaft of the clutch to transmit a driving torque from the output shaft of the transmission to the drive wheels. An engine temperature sensor is provided for detecting an engine temperature. An electronic control unit is connected to the propulsion mechanism and the engine temperature sensor, for disengaging the clutch and stopping the engine during a standstill state of the hybrid vehicle, and for propelling the hybrid vehicle by a driving torque generated by the second electric motor when the hybrid vehicle starts, and for starting up the engine by the first electric motor and engaging the clutch after engine startup, during the warm-up of the engine. A variable valve timing control system is electrically connected to the control unit for adjusting an intake-valve closure timing to a predetermined retarded closure timing when the clutch is disengaged and for adjusting the intake-valve closure timing to a predetermined advanced closure timing after the clutch is engaged, after the engine warm-up.

6 Claims, 12 Drawing Sheets

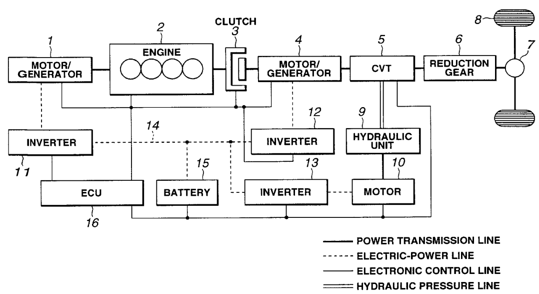


Figure 7: Patent example

US006727670B1

(12) **United States Patent**
Grabowski et al.

(10) **Patent No.:** **US 6,727,670 B1**
(45) **Date of Patent:** **Apr. 27, 2004**

(54) **BATTERY CURRENT LIMITER FOR A HIGH VOLTAGE BATTERY PACK IN A HYBRID ELECTRIC VEHICLE POWERTRAIN**

(75) Inventors: **John Robert Grabowski**, Dearborn, MI (US); **Michael W. Degner**, Novi, MI (US)

(73) Assignee: **Ford Global Technologies, LLC**, Dearborn, MI (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **10/248,035**

(22) Filed: **Dec. 12, 2002**

(51) **Int. Cl.**[7] **H02P 7/00**
(52) **U.S. Cl.** **318/432**; 318/139; 701/22; 320/121
(58) **Field of Search** 318/432, 139; 701/22; 320/121

(56) **References Cited**

U.S. PATENT DOCUMENTS

5,569,999	A	*	10/1996	Boll et al.	320/136
5,635,805	A		6/1997	Ibaraki et al.	318/139
5,697,466	A		12/1997	Moroto et al.	180/65.2
5,713,814	A		2/1998	Hara et al.	477/5
5,820,172	A		10/1998	Brigham et al.	290/40
5,842,534	A		12/1998	Frank	180/65.2
5,998,952	A	*	12/1999	McLaughlin et al.	318/432
6,026,921	A		2/2000	Aoyama et al.	180/65.2
6,164,400	A		12/2000	Jankovic et al.	180/65.2
6,176,808	B1		1/2001	Brown et al.	477/5
6,215,198	B1		4/2001	Inada et al.	290/40
6,223,106	B1		4/2001	Yano et al.	701/22
6,232,744	B1	*	5/2001	Kawai et al.	320/132
6,232,748	B1		5/2001	Kinoshita	320/132
6,253,140	B1		6/2001	Jain et al.	701/67
6,393,350	B1	*	5/2002	Light et al.	701/54
2003/0088343	A1	*	5/2003	Ochiai et al.	701/22

* cited by examiner

Primary Examiner—Rita Leykin
(74) *Attorney, Agent, or Firm*—Brooks & Kushman; Carlos Hanze

(57) **ABSTRACT**

A battery current limiter and current-limiting method for a battery system and an electric motor in a hybrid automotive vehicle powertrain. The battery current limiter monitors measured battery current and torque commands. A modified current is developed to take a predetermined current margin into account. The modified current reduces battery current in a closed loop fashion simultaneously with a reduction in commanded torque by a feed-forward torque value.

6 Claims, 3 Drawing Sheets

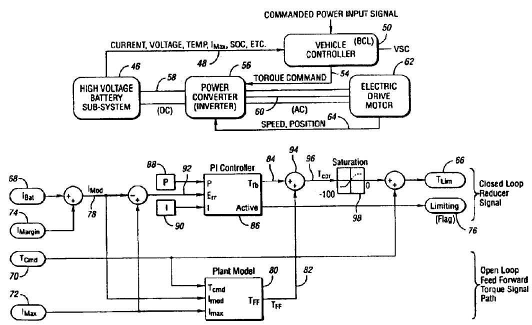


Figure 8: Patent example

US008036340B2

(12) United States Patent
Soto Santos

(10) Patent No.: US 8,036,340 B2
(45) Date of Patent: Oct. 11, 2011

(54) **X-RAY APPARATUS**

(75) Inventor: **Jose-Emilio Soto Santos**, Paris (FR)

(73) Assignee: **General Electric Company**, Schenectady, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 215 days.

(21) Appl. No.: **12/171,314**

(22) Filed: **Jul. 11, 2008**

(65) **Prior Publication Data**

US 2009/0034686 A1 Feb. 5, 2009

(30) **Foreign Application Priority Data**

Jul. 19, 2007 (FR) 07 56591

(51) **Int. Cl.**
H05G 1/34 (2006.01)

(52) **U.S. Cl.** **378/109**; 378/101; 378/102; 378/103; 378/106; 378/110; 378/111; 378/112

(58) **Field of Classification Search** 378/106, 378/101–103, 109–112
See application file for complete search history.

(56) **References Cited**

U.S. PATENT DOCUMENTS

4,477,761	A	10/1984	Wolf	
5,283,512	A	2/1994	Stadnick et al.	
6,075,331	A	6/2000	Ando et al.	
6,282,260	B1 *	8/2001	Grodzins	378/87
6,727,670	B1	4/2004	Grabowski et al.	
2003/0107352	A1 *	6/2003	Downer et al.	322/40

FOREIGN PATENT DOCUMENTS

DE	10 2005 052 115	A1	5/2007
EP	0 946 082	A1	9/1999
JP	61-267300		11/1986

* cited by examiner

Primary Examiner — Hoon Song
Assistant Examiner — Mona M Sanei
(74) *Attorney, Agent, or Firm* — Global Patent Operation; Jonathan E. Thomas

(57) **ABSTRACT**

An X-ray apparatus includes a converter into which there is integrated a control logic circuit configured to regulate the supply voltage of a high-voltage power supply source of the X-ray apparatus. To this end, the intelligent voltage-voltage, converter is placed between the power battery and the capacitor bank. This intelligent converter is capable of determining the optimum voltage to be delivered to the generator for the radiology examination to be undertaken in regulating the current of the power battery at the necessary level of current.

9 Claims, 3 Drawing Sheets

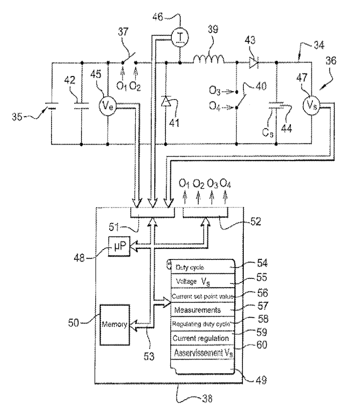
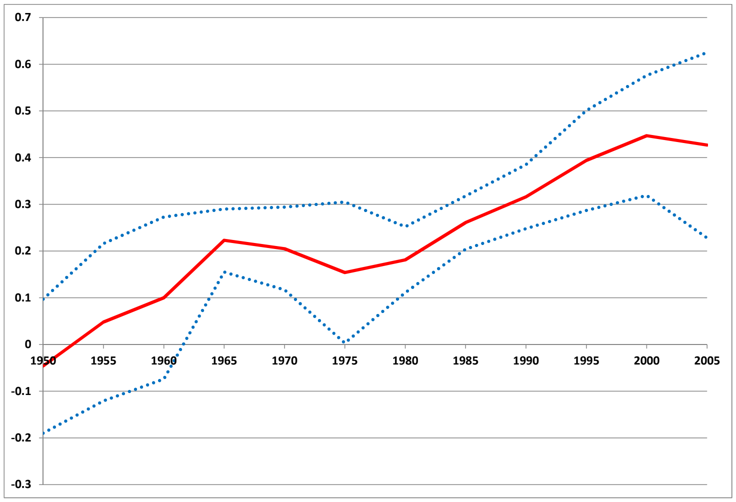


Figure 9: The gap in knowledge spillovers between 1950 and 2005 using PatentRank



PatentRank Results

Figure 10: The gap in knowledge spillovers between 1950 and 2005 using PatentRank

(a) No future patents (b) Future patents

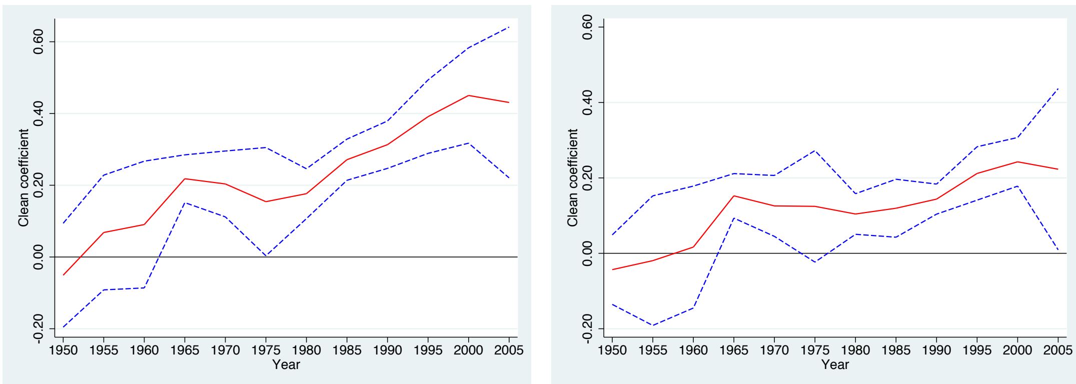


Figure 11: The gap in knowledge spillovers between 1950 and 2005 using PatentRank within 5 years window

(a) No future patents (b) Future patents

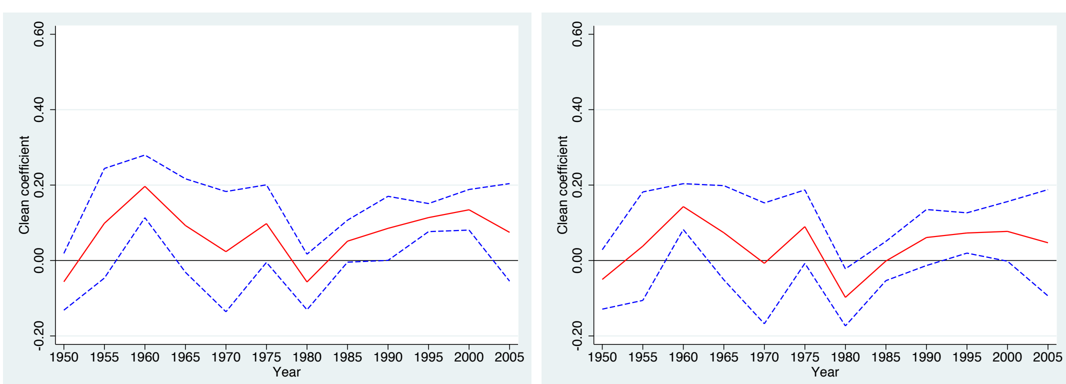
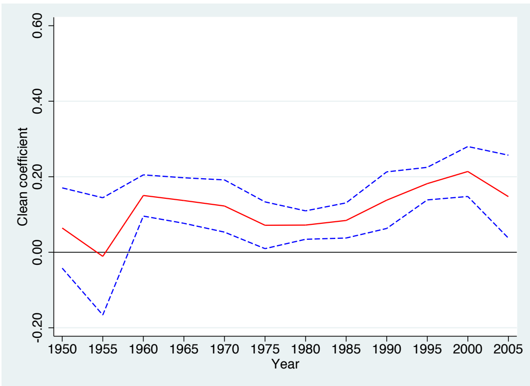


Figure 12: The gap in knowledge spillovers between 1950 and 2005 using PatentRank across IPC3 codes

(a) No future patents



(b) Future patents

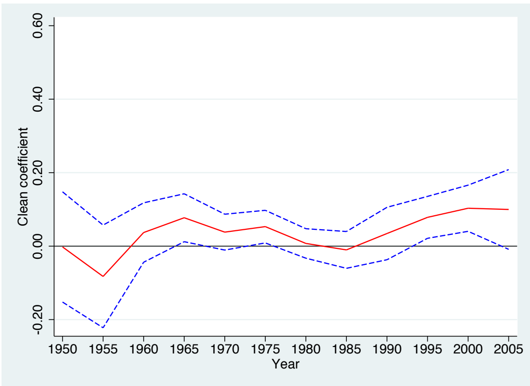


Table 23: Clean, Grey and True Dirty

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	PatentRank index			
Clean/Grey invention	0.292***	0.121***	0.190***	0.331***
	(0.014)	(0.012)	(0.016)	(0.015)
Number of patents	-0.031***	-0.006	-0.084***	-0.029***
	(0.005)	(0.008)	(0.004)	(0.005)
Family size	0.067***	0.059***	0.065***	0.065***
	(0.003)	(0.006)	(0.004)	(0.003)
Triadic	0.241***	0.278***	0.238***	0.240***
	(0.025)	(0.045)	(0.028)	(0.026)
Granted	0.491***	0.520***	0.508***	0.456***
	(0.021)	(0.022)	(0.022)	(0.019)
Observations	1,149,988	326,942	978,179	1,006,996

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the PatentRank index. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Figure 13: Clean, grey, dirty, and radically new technologies vs. all other technologies - PageRank index

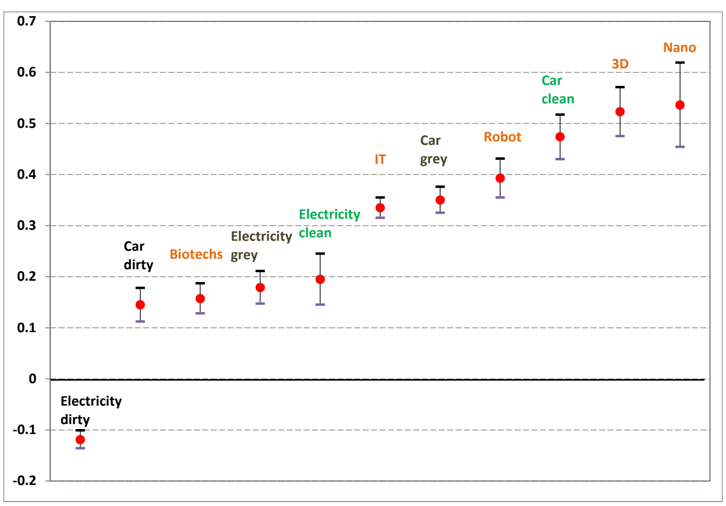


Table 24: Within vs. across-country spillovers

	(1)	(2)	(3)
Dep. var.	PatentRank	PatentRank for "national" citations	PatentRank for "international" citations
Clean invention	0.292***	0.285***	0.361***
	(0.014)	(0.017)	(0.013)
Number of patents	-0.031***	-0.035***	-0.042***
	(0.005)	(0.006)	(0.005)
Family size	0.067***	0.062***	0.073***
	(0.003)	(0.003)	(0.003)
Triadic	0.241***	0.240**	0.331***
	(0.026)	(0.020)	(0.033)
Granted	0.491***	0.435***	0.731***
	(0.021)	(0.016)	(0.028)
Obs.	1,149,988	1,149,988	1,149,988

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variables are the PatentRank index (column 1), the PatentRank index on the pool of national citations (column 2), and the PatentRank index on the pool of international citations (column 3). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 25: Government spending

	(1)	(2)	(3)	(4)	(5)	(6)
Sample	All		Transport		Electricity	
Dep. var.	PatentRank index					
Clean invention	0.345***	0.353***	0.153**	0.149**	0.339**	0.347**
	(0.028)	(0.026)	(0.052)	(0.052)	(0.028)	(0.026)
Government spending		0.022***		-0.020		0.021**
		(0.007)		(0.155)		(0.006)
Number of patents	0.012	0.013	-0.040**	-0.040**	0.013	0.014
	(0.008)	(0.008)	(0.015)	(0.015)	(0.008)	(0.008)
Family size	0.060***	0.059***	0.057***	0.057***	0.059***	0.059***
	(0.004)	(0.004)	(0.015)	(0.015)	(0.004)	(0.004)
Triadic	0.285***	0.284***	0.391***	0.394***	0.274***	0.273***
	(0.037)	(0.037)	(0.076)	(0.076)	(0.037)	(0.037)
Granted	0.360***	0.360***	0.534***	0.535***	0.359***	0.358***
	(0.017)	(0.017)	(0.032)	(0.032)	(0.017)	(0.017)
Obs.	497,439	497,439	16,719	16,719	489,531	489,531

Source: International Energy Agency (2013): Energy Technology Research and Development Database (Edition: 2013). Mimas, University of Manchester

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the PatentRank index. The sample includes clean and dirty inventions from the transport sector (columns 3 and 4), electricity sector (columns 5 and 6) and both transport and electricity sectors (columns 1 and 2) . All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 26: Government spending

	(1)	(2)	(3)	(4)
Sample	Transport		Electricity	
Dep. var.	Citations received			
Clean invention	0.253**	0.253***	0.483***	0.497***
	(0.077)	(0.079)	(0.026)	(0.026)
Government spending		-0.001		0.032***
		(0.033)		(0.007)
Number of patents	-0.070***	-0.070***	-0.006	-0.005
	(0.020)	(0.020)	(0.009)	(0.009)
Family size	0.054***	0.054***	0.066***	0.066***
	(0.012)	(0.012)	(0.004)	(0.004)
Triadic	0.474***	0.474***	0.447***	0.445***
	(0.093)	(0.094)	(0.046)	(0.047)
Granted	0.776***	0.776***	0.696***	0.695***
	(0.055)	(0.055)	(0.026)	(0.026)
Obs.	16,703	16,703	488,896	488,896

Source: International Energy Agency (2013): Energy Technology Research and Development Database (Edition: 2013). Mimas, University of Manchester
Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received excluding self-citations by inventors. The sample includes clean and dirty inventions from the transport sector (columns 3 and 4), electricity sector (columns 5 and 6) and both transport and electricity sectors (columns 1 and 2) . All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 27: University and Firms

	(1)	(2)
Dep. var.	PatentRank index	
Clean invention	0.293***	0.298***
	(0.013)	(0.013)
Number of patents	-0.019***	-0.022***
	(0.004)	(0.004)
Family size	0.063***	0.060***
	(0.003)	(0.003)
Triadic	0.237***	0.229***
	(0.024)	(0.024)
Granted	0.561***	0.552***
	(0.021)	(0.021)
University		0.276***
		(0.014)
Firms		0.206***
		(0.011)
Obs.	826,078	826,078

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received excluding self-citations by inventors (columns 1 and 2) and the PatentRank index (columns 3 and 4). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 28: University, firms, and private individuals

	(1)	(2)	(3)
Applicant	University	Firm	Individual
Dep. var.		PatentRank index	
Clean invention	0.311***	0.290***	0.331***
	(0.016)	(0.014)	(0.019)
Number of patents	-0.040***	-0.015***	-0.049***
	(0.006)	(0.005)	(0.007)
Family size	0.056***	0.060***	0.289***
	(0.005)	(0.003)	(0.036)
Triadic	0.096**	0.239***	-0.614
	(0.030)	(0.025)	(0.340)
Granted	0.411***	0.571***	0.088***
	(0.030)	(0.022)	(0.025)
Obs.	36,186	706,517	75,487

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received excluding self-citations by inventors (columns 1 to 3) and the PatentRank index (columns 4 to 6). The sample includes inventions which have universities (column 1 and 4), firms (column 2 and 5), or individuals (column 3 and 6) as applicants. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 29: Adding inventor and inventor fixed effect

	(1)	(2)	(3)	(4)
Dep. var.	PatentRank index			
Clean invention	0.216***	0.259***	0.274***	0.272***
	(0.004)	(0.006)	(0.017)	(0.027)
Number of patents	-0.028***	-0.023***	-0.002	-0.024***
	(0.002)	(0.003)	(0.007)	(0.008)
Family size	0.027***	0.077***	0.082***	0.085***
	(0.002)	(0.004)	(0.006)	(0.009)
Triadic	0.598***	0.405***	0.250***	0.254***
	(0.009)	(0.015)	(0.042)	(0.056)
Granted	0.721***	0.572***	0.562***	0.574***
	(0.005)	(0.007)	(0.024)	(0.025)
fixed effect	no	inventor	no	applicant
Obs.	697,192	697,192	435,584	435,584

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received excluding self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office, sector, year and month fixed effects.

Table 30: Intra vs. inter-sectoral spillovers

	(1)	(2)	(3)
Dep. var.	PatentRank	PatentRank intra-sectoral	PatentRank inter-sectoral
Clean invention	0.292***	0.336***	0.248***
	(0.014)	(0.016)	(0.016)
Number of patents	-0.031***	-0.044***	-0.160***
	(0.005)	(0.006)	(0.007)
Family size	0.067***	0.067***	0.068***
	(0.003)	(0.003)	(0.003)
Triadic	0.241***	0.246***	0.259***
	(0.026)	(0.025)	(0.025)
Granted	0.491***	0.456***	0.521***
	(0.021)	(0.021)	(0.017)
Obs.	1,149,988	1,149,988	1,149,988

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variables are PatentRank index (column 1), PatentRank index on citations within their own technological field (based on IPC 3 digit code) (column 2), and the PatentRank index on citations across across technological field (column 3). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 31: Generality and originality as controls

	(1)	(2)	(3)	(4)
Dep. var.	PatentRank index			
Clean invention	0.193***	0.179***	0.193***	0.178***
	(0.007)	(0.007)	(0.007)	(0.007)
Number of patents	-0.010***	0.019***	-0.003	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)
Family size	0.026***	0.022***	0.025***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)
Triadic	0.130***	0.110***	0.127***	0.111***
	(0.007)	(0.006)	(0.007)	(0.006)
Granted	0.245***	0.203***	0.240***	0.204***
	(0.010)	(0.010)	(0.010)	(0.010)
Generality		0.628***		0.663***
		(0.010)		(0.010)
Originality			0.127***	-0.097***
			(0.006)	(0.008)
Obs.	281,978	281,978	281,978	281,978

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 32: Controlling for age of technological field

	(1)	(2)	(3)	(4)
Dep. var.	PatentRank index			
Clean invention	0.283***	0.267***	0.257***	0.247***
	(0.013)	(0.013)	(0.013)	(0.012)
Number of patents	-0.053***	-0.029***	-0.023***	-0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
Family size	0.065***	0.063***	0.063***	0.063***
	(0.003)	(0.003)	(0.003)	(0.003)
Triadic	0.236***	0.227***	0.210***	0.202***
	(0.025)	(0.025)	(0.025)	(0.025)
Granted	0.487***	0.480***	0.474***	0.470***
	(0.021)	(0.021)	(0.020)	(0.020)
Age of tech field		-0.117***	0.233***	
		(0.006)	(0.014)	
Age of tech field^2			-0.023***	
			(0.001)	
Age of tech dummies	no	no	no	yes
Observations	1,149,237	1,149,237	1,149,237	1,149,237

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the PatentRank index. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 33: Spillovers from clean and other new technologies

	(1)	(2)	(3)	(4)	(5)
Baseline sector	IT	Biotechs	Nano	Robot	3D
Dep. var.			PatentRank index		
Clean invention	-0.039	0.131***	-0.249***	-0.096*	-0.120***
	(0.028)	(0.023)	(0.040)	(0.043)	(0.018)
Number of patents	-0.031***	-0.029***	0.023***	0.014	0.018*
	(0.005)	(0.006)	(0.008)	(0.078)	(0.008)
Family size	0.017***	0.029***	0.052***	0.053***	0.052***
	(0.003)	(0.004)	(0.006)	(0.006)	(0.006)
Triadic	0.421***	0.435***	0.329***	0.337***	0.333***
	(0.050)	(0.042)	(0.055)	(0.054)	(0.055)
Granted	0.604***	0.413***	0.441***	0.443***	0.448***
	(0.040)	(0.017)	(0.025)	(0.025)	(0.025)
Observations	1,445,552	403,294	180,441	198,602	185,726

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the PatentRank index. The sample includes all clean patents (transport and electricity) and patents from the following technologies: IT (column 1), biotechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 34: Comparing spillovers from clean and dirty within new technologies

	(1)	(2)	(3)	(4)	(5)
Sector	IT	Biotechs	Nano	Robot	3D
Dep. var.	PatentRank index				
Clean invention	0.129*	0.422***	0.189	0.349	0.290
	(0.053)	(0.067)	(0.100)	(0.325)	(0.461)
Number of patents	-0.037***	-0.074***	0.033	-0.062**	-0.080***
	(0.006)	(0.005)	(0.023)	(0.023)	(0.014)
Family size	0.017***	0.028***	0.070***	0.088***	0.056***
	(0.003)	(0.004)	(0.013)	(0.009)	(0.011)
Triadic	0.401***	0.406***	0.341***	0.261***	0.305**
	(0.049)	(0.041)	(0.070)	(0.057)	(0.060)
Granted	0.624***	0.342***	0.424***	0.443***	0.571***
	(0.044)	(0.019)	(0.075)	(0.042)	(0.044)
Observations	1,270,842	227,100	1,481	22,266	9,359

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the PatentRank. The sample includes patents from the following technologies: IT (column 1), bioechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 35: Spillovers from clean and CCS technologies

Dep. var.	PatentRank index
Clean invention	0.045
	(0.023)
Number of patents	0.057***
	(0.010)
Family size	0.055***
	(0.005)
Triadic	0.271***
	(0.047)
Granted	0.338***
	(0.019)
Observations	106,700

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes clean electricity production inventions and CO2 Capture and Storage technology. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 36: Clean, Grey and true Dirty - Transport

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	Citations received			
Clean/Grey invention	0.347***	0.118***	0.304***	0.481***
	(0.018)	(0.020)	(0.017)	(0.022)
Number of patents	-0.068***	-0.144***	-0.109***	-0.082***
	(0.009)	(0.010)	(0.009)	(0.009)
Family size	0.070***	0.070***	0.081***	0.065***
	(0.008)	(0.011)	(0.010)	(0.007)
Triadic	0.521***	0.483***	0.474***	0.488***
	(0.056)	(0.071)	(0.059)	(0.055)
Granted	1.134***	1.122***	1.173***	1.046***
	(0.034)	(0.041)	(0.036)	(0.032)
Observations	419,959	207,524	345,313	287,469

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions all in the transport sector. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Clean, Grey and True Dirty

Table 37: Clean, Grey and true Dirty - Transport

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	PatentRank index			
Clean/Grey invention	0.219***	0.090***	0.169***	0.292***
	(0.014)	(0.014)	(0.017)	(0.018)
Number of patents	-0.048***	-0.075***	-0.088***	-0.053***
	(0.006)	(0.006)	(0.006)	(0.005)
Family size	0.062***	0.059***	0.074***	0.057***
	(0.007)	(0.010)	(0.007)	(0.006)
Triadic	0.279***	0.281***	0.219***	0.284***
	(0.046)	(0.057)	(0.040)	(0.046)
Granted	0.620***	0.599***	0.637***	0.588***
	(0.027)	(0.027)	(0.029)	(0.024)
Observations	419,959	207,524	345,313	287,469

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is PatentRank index. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions all in the transport sector. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 38: Clean, Grey and true Dirty - Electricity

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	Citations received			
Clean/Grey invention	0.488***	0.188***	0.262***	0.499***
	(0.023)	(0.032)	(0.019)	(0.023)
Number of patents	-0.047***	0.042***	-0.114***	-0.044***
	(0.009)	(0.011)	(0.007)	(0.009)
Family size	0.067***	0.070***	0.066***	0.067***
	(0.004)	(0.004)	(0.004)	(0.004)
Triadic	0.432***	0.416***	0.396***	0.438***
	(0.050)	(0.051)	(0.046)	(0.050)
Granted	0.725***	0.660***	0.738***	0.727***
	(0.024)	(0.029)	(0.026)	(0.025)
Observations	748,918	120,752	647,541	733,859

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, corrected for self-citations by inventors. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions all in the electricity production sector. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 39: Clean, Grey and true Dirty - Electricity

	(1)	(2)	(3)	(4)
Sample	Clean vs. Grey and true Dirty	Clean vs. Grey	Grey vs. True Dirty	Clean vs. True Dirty
Dep. var.	PatentRank index			
Clean/Grey invention	0.333***	0.046	0.287***	0.342***
	(0.023)	(0.028)	(0.013)	(0.023)
Number of patents	-0.019***	0.062***	-0.073***	-0.015*
	(0.007)	(0.010)	(0.004)	(0.007)
Family size	0.060***	0.058***	0.061***	0.061***
	(0.004)	(0.003)	(0.004)	(0.005)
Triadic	0.252***	0.228***	0.226***	0.256***
	(0.000)	(0.038)	(0.037)	(0.042)
Granted	0.381***	0.331***	0.393***	0.382***
	(0.017)	(0.018)	(0.018)	(0.017)
Observations	748,918	120,752	647,541	733,859

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the PatentRank index. The sample includes clean, grey and truly dirty (column 1), clean and grey (column 2), grey and truly dirty (column 3), and clean and truly dirty (column 4) inventions all in the electricity production sector. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 40: Generality and originality as controls

	(1)	(2)	(3)	(4)
Dep. var.		Citations received		
Clean invention	0.365***	0.332***	0.363***	0.332***
	(0.012)	(0.012)	(0.012)	(0.012)
Number of patents	-0.044***	0.007	-0.025***	0.006
	(0.005)	(0.006)	(0.005)	(0.005)
Family size	0.043***	0.039***	0.041***	0.039***
	(0.002)	(0.002)	(0.002)	(0.002)
Triadic	0.296***	0.264***	0.287***	0.264***
	(0.014)	(0.013)	(0.014)	(0.013)
Granted	0.673***	0.591***	0.659***	0.592***
	(0.023)	(0.021)	(0.022)	(0.021)
Generality		1.149***		1.164***
		(0.019)		(0.019)
Originality			0.371***	-0.036*
			(0.015)	(0.015)
Obs.	281,978	281,978	281,978	281,978

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received, corrected for self-citations by inventors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year and month fixed effects.

Table 41: Comparing the generality of clean and other new technologiess

	(1)	(2)	(3)	(4)	(5)
Sector	IT	Biotechs	Nano	Robot	3D
Dep. var.			Originality measure		
Clean invention	-0.050***	-0.059***	0.009	-0.130***	-0.184***
	(0.004)	(0.004)	(0.018)	(0.004)	(0.006)
Number of patents	-0.070***	-0.033***	-0.049***	-0.051***	-0.051***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Family size	0.003***	0.002***	0.005***	0.005***	0.005***
	(0.0004)	(0.0003)	(0.001)	(0.001)	(0.001)
Triadic	0.010***	0.005	0.014***	0.015***	0.014**
	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)
Granted	0.020***	-0.003	0.029***	0.027***	0.027***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	520,978	155,701	59,651	67,115	62,559

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the originality measure. The sample includes all clean inventions (automobile and electricity production sectors) and inventions from the following technologies: IT (column 1), biotechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by OLS and include patent office-by-year and month fixed effects.

Table 42: Comparing the generality of clean and other new technologiess

	(1)	(2)	(3)	(4)	(5)
Sector	IT	Biotechs	Nano	Robot	3D
Dep. var.			Generality measure		
Clean invention	-0.047***	-0.052***	0.009	-0.126***	-0.204***
	(0.004)	(0.004)	(0.022)	(0.004)	(0.006)
Number of patents	-0.063***	-0.034***	-0.048***	-0.050***	-0.050***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Family size	0.004***	0.003***	0.008***	0.008***	0.008***
	(0.0005)	(0.0003)	(0.001)	(0.001)	(0.001)
Triadic	0.013***	0.016***	0.022***	0.023***	0.020***
	(0.002)	(0.003)	(0.005)	(0.005)	(0.004)
Granted	0.022***	0.022***	0.041***	0.038***	0.039***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Observations	723,257	207,073	94,437	103,972	98,461

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the generality measure. The sample includes all clean patents (automobile and electricity production sectors) and patents from the following technologies: IT (column 1), biotechs (column 2), nano (column 3), robot (column 4), and 3D (column 5). All columns are estimated by OLS and include patent office-by-year and month fixed effects.

Table 43: Five-year window

	(1)	(2)	(3)	(4)	(5)	(6)
Sector	All	Transport	Electricity	All	Transport	Electricity
Dep. var.	Citations received within 5-year window			PatentRank within 5-year window		
Clean invention	0.382***	0.284***	0.474***	0.210***	0.140***	0.248***
	(0.021)	(0.025)	(0.034)	(0.015)	(0.014)	(0.026)
Number of patents	-0.038***	-0.055***	-0.023*	-0.038***	-0.059***	-0.022**
	(0.008)	(0.001)	(0.010)	(0.005)	(0.006)	(0.007)
Family size	0.075***	0.070***	0.063***	0.069***	0.062***	0.059***
	(0.003)	(0.001)	(0.007)	(0.003)	(0.008)	(0.006)
Triadic	0.508***	0.557***	0.515***	0.306***	0.354***	0.346***
	(0.043)	(0.070)	(0.068)	(0.003)	(0.053)	(0.053)
Granted	1.005***	1.181***	0.756***	0.581***	0.693***	0.473***
	(0.040)	(0.054)	(0.035)	(0.024)	(0.036)	(0.022)
Observations	1,162,220	419,959	748,918	1,162,220	419,959	748,918

Notes: Robust standard errors in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received within a five-year period after the publication year, corrected for self-citations by inventors (columns 1 to 3) and the PatentRank index on the sample of citations within five years (columns 4 to 6). The sample includes patents which have cited clean or dirty technologies in the automobile sector (columns 2 and 4), electricity sector (columns 3 and 6), and both (colunns 1 and 4). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Robustness Checks

Five years window

As in section 2.4 we look at the number of citations received within a five-year window to at least partially overcome the truncation bias that is due to the fact that we observe citations for only a portion of the life of an invention, with the duration of that portion varying across patent cohorts (see Table 43). The coefficients obtained for the clean dummy barely change.

Discarding citations

We discard citations added by patent examiners in Table 44.[27]By restricting the citation counts to the ones made by the applicant only, we address the concern that patent citations added by examiners might not capture actual knowledge spillovers. The results obtained when all sectors are pooled together barely change but the only noticeable difference is that the clean dummy is no longer significant on the fuel sector when citations added by examiners are excluded. Jaffe and Trajtenberg (1999)) find that patent assigned to the same firm are more likely to cite each other. We therefore correct for self-citations at the level of the applicant (the firm or the individual who filed the patent) rather than at the level of individual inventors in Table 45. The results don't change qualitatively.

[27]Note that we restrict the sample to patent offices for which distinction between citation added by patent examiner or applicant is made.

Table 44: Citations made by *applicants* only

	(1)	(2)	(3)	(4)	(5)	(6)
Sector	All	Transport	Electricity	All	Transport	Electricity
Dep. var.	Citations received excl. citations added by patent examiner			PatentRank index excl. citations added by patent examiner		
Clean invention	0.624***	0.582***	0.659***	0.041***	0.013	0.085***
	(0.018)	(0.025)	(0.026)	(0.009)	(0.011)	(0.009)
Number of patents	-0.010	-0.036***	0.007	-0.016***	-0.016***	-0.018***
	(0.008)	(0.011)	(0.011)	(0.002)	(0.003)	(0.003)
Family size	0.070***	0.070***	0.060***	0.012***	0.017***	0.008***
	(0.003)	(0.007)	(0.004)	(0.001)	(0.002)	(0.001)
Triadic	0.516***	0.537***	0.564***	0.072***	0.049***	0.098***
	(0.042)	(0.064)	(0.066)	(0.008)	(0.009)	(0.011)
Granted	1.144***	1.164***	1.101***	0.102***	0.097***	0.105***
	(0.025)	(0.035)	(0.031)	(0.007)	(0.009)	(0.012)
Observations	1,162,220	419,950	748,918	1,162,220	419,950	748,918

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, excluding citations made by the patent examiners and corrected for self-citations by inventors (columns 1 to 3) and the PatentRank index on the sample of citations excluding the ones made by the patent examiners (colums 4 to 6). The sample only includes patent offices for which the information on whether citations are added by the applicant or the patent examiner are available. The sample includes patents which have cited clean or dirty technologies in the automobile sector (columns 2 and 4), electricity production sector (columns 3 and 6), in both (columns 1 and 4). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Table 45: Excluding self-citations at applicant level

	(1)	(2)	(3)	(4)	(5)	(6)
Sector	All	Transport	Electricity	All	Transport	Electricity
Dep. var.	Citations received corrected for self-citations at applicant level			PatentRank index corrected for self-citations at applicant level		
Clean invention	0.363***	0.351***	0.350***	0.164***	0.161***	0.155***
	(0.013)	(0.022)	(0.016)	(0.007)	(0.011)	(0.010)
Number of patents	-0.040***	-0.030***	-0.047***	0.0004	0.002	0.001
	(0.005)	(0.007)	(0.007)	(0.003)	(0.004)	(0.004)
Family size	0.044***	0.046***	0.038***	0.033***	0.033***	0.030***
	(0.003)	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)
Triadic	0.218***	0.250***	0.214**	0.114***	0.103***	0.135**
	(0.024)	(0.039)	(0.030)	(0.013)	(0.019)	(0.015)
Granted	0.456***	0.549***	0.388***	0.201***	0.242***	0.168***
	(0.016)	(0.019)	(0.022)	(0.010)	(0.013)	(0.013)
Observations	421,872	167,711	244,435	421,872	167,711	244,435

Notes: Robust standard errors, p-values in parentheses (* $p<0.05$, ** $p<0.01$, *** $p<0.001$). The dependent variable is the total number of citations received, corrected for self-citations at the applicant level (columns 1 to 3) and the PatentRank index on the sample of citations excluding self-citations at the appliant level (colums 4 to 6). The sample includes patents which have cited clean or dirty technologies in the automobile sector (columns 2 and 4), electricity production sector (columns 3 and 6), in both (columns 1 and 4). All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Additional controls

We add a number of additional controls variables for patent quality in Table 46. The claims specify the components of the patent invention and hence represent the scope of the invention (Lanjouw and Schankerman (1999)). This information is only available in our patent database for a limited number of patent offices, implying that our sample size is significantly reduced. For this reason we do not include the number of claims in our baseline regressions, but overall the results barely change (coefficient on clean = 0.403***). The number of IPC3 codes is added in order to control for the fact that certain inventions belong to multiple IPC codes. These inventions are likely to be more general and therefore more cited. This effect however does not appear to downplay the clean advantage in terms of spillovers. Finally, we add the number of inventors and still find that clean inventions are

Table 46: Additional controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			Citations received			
Clean invention	0.404***	0.432***	0.427***	0.432***	0.428***	0.432***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)
Number of patents	-0.032***	-0.020***	-0.005***	-0.049***	-0.057***	-0.013
	(0.005)	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
Family size	0.033***	0.065***	0.061***	0.062***	0.056***	0.013***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)
Triadic	0.239***	0.464***	0.281***	0.401***	0.447***	0.229***
	(0.012)	(0.042)	(0.022)	(0.029)	(0.034)	(0.019)
Granted	0.750***	0.938***	0.922***	0.894***	0.941***	0.855***
	(0.025)	(0.000)	(0.028)	(0.030)	(0.030)	(0.028)
# claims	0.010***					
	(0.0004)					
# IPC 3		0.103***				0.092***
		(0.013)				(0.005)
# inventors			0.321***			0.341***
			(0.014)			(0.167)
# citations made				0.018***		0.017***
				(0.001)		(0.001)
# applicants					0.009***	-0.008***
					(0.0010)	(0.001)
Obs.	175,298	1,161,160	865,607	1,161,160	1,161,160	

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, excluding self-citations by the inventor (columns 1 to 3) and the PatentRank index on the sample of citations excluding self-citations by the inventor (colums 4 to 6). The sample includes clean or dirty technologies in the automobile and electricity production sectors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Table 47: Additional controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			PatentRank index			
Clean invention	0.239***	0.295***	0.294***	0.294***	0.291***	0.298***
	(0.009)	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)
Number of patents	-0.0002	-0.005	-0.022***	-0.027***	-0.031***	0.003***
	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Family size	0.021***	0.061***	0.023***	0.059***	0.058***	0.023***
	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)
Triadic	0.120***	0.244***	0.138***	0.193***	0.236***	0.095***
	(0.005)	(0.030)	(0.017)	(0.022)	(0.026)	(0.014)
Granted	0.336***	0.484***	0.517***	0.462***	0.488***	0.475***
	(0.016)	(0.021)	(0.018)	(0.019)	(0.021)	(0.017)
# claims	0.004***					
	(0.0002)					
# IPC 3		0.077***				0.062***
		(0.007)				(0.003)
# inventors			0.216***			0.238***
			(0.009)			(0.010)
# citations made				0.014***		0.012***
				(0.001)		(0.001)
# applicants					0.006***	-0.008
					(0.002)	(0.001)
Obs.	175,298	1,161,160	865,607	1,161,160	1,161,160	

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the PatentRank index on the sample of citations received, excluding self-citations by the inventor. The sample includes clean or dirty technologies in the automobile and electricity production sectors. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects

Table 48: Different subsamples

	(1)	(2)	(3)	(4)
Sample	nozero	triadic	US patent office	EU patent office
Dep. var.		Citations received		
Clean invention	0.321***	0.387***	0.429***	0.491***
	(0.012)	(0.019)	(0.019)	(0.050)
Number of patents	-0.045***	-0.041***	-0.054***	-0.010
	(0.005)	(0.008)	(0.009)	(0.019)
Family size	0.056***	0.021***	0.049***	0.048***
	(0.002)	(0.002)	(0.003)	(0.011)
Triadic	0.365***		0.134***	0.447***
	(0.022)		(0.021)	(0.048)
Granted	0.625***	0.663***	0.957***	0.641***
	(0.025)	(0.045)	(0.069)	(0.045)
Observations	514,865	45,129	134,664	10,248

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the total number of citations received, excluding self-citations by the inventor The sample includes (i) patents that receive at least one citation in column 1; (ii) triadic patents (filed at EPO, USPTO and JPO) in column 2; (iii) patents first filed in the US patent office only in column 3; (iv) patents first filed in the European patent office only in column 4. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Various subsamples

In Table 48 we look at different subsamples. We start by restricting the sample to patents that received at least one citation. Given that a large fraction of patents (69%) are never cited, spillovers from clean technologies might be biased if there are disproportionately more dirty patents that are never cited. We also look at highly valuable inventions by focusing on triadic patents (i.e., patents that have been filed at the USPTO, the EPO and the Japan Patent Office, see above). This can give us some insight into whether the clean advantage is still present for the upper part of the distribution. In addition, we restrict our sample to patents filed at the US patent office and at the European Patent Office. None of these tests modify our main finding (coefficient on clean between 0.319*** and 0.469***).

Table 49: Different subsamples

	(1)	(2)	(3)	(4)
Sample	nozero	triadic	US patent office	EU patent office
Dep. var.		PatentRank index		
Clean invention	0.173***	0.212***	0.254***	0.340***
	(0.008)	(0.009)	(0.014)	(0.032)
Number of patents	-0.013***	-0.003	-0.016***	-0.007
	(0.002)	(0.003)	(0.004)	(0.008)
Family size	0.039***	0.007***	0.031***	0.038***
	(0.002)	(0.001)	(0.002)	(0.003)
Triadic	0.164***		0.070***	0.234***
	(0.013)		(0.010)	(0.023)
Granted	0.249***	0.294***	0.573***	0.337***
	(0.016)	(0.024)	(0.040)	(0.026)
Observations	514,865	45,129	134,664	10,248

Notes: Robust standard errors, p-values in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the PatentRank index on the sample of citations received, corrected for self-citations by inventors. The sample includes (i) patents that receive at least one citation in column 1; (ii) triadic patents (filed at EPO, USPTO and JPO) in column 2; (iii) patents first filed in the US patent office only in column 3; (iv) patents first filed in the European patent office only in column 4. All columns are estimated by Poisson pseudo-maximum likelihood and include patent office-by-year-by-sector fixed effects, and month fixed effects.

Table 50: Estimation of Tobin's Q equation - By field or country

	(1)	(2)	(3)	(4)
Dep. var.	ln Tobin's Q			
Subsample	Manufacturing		USA	
ln (R&D / assets)	0.442***	0.075	0.319***	0.236***
	(0.037)	(0.048)	(0.040)	(0.028)
ln (Patent / R&D)	0.024	-0.013	3.063	-1.004
	(0.048)	(0.038)	(1.908)	(1.922)
ln (Fwd citations / patent)	0.073***	0.087***	0.041*	0.137***
	(0.013)	(0.017)	(0.022)	(0.033)
ln (Bwd clean citations / patent)	0.121***	0.171*	0.173**	0.479***
	(0.045)	(0.088)	(0.078)	(0.135)
ln (Bwd dirty citations / patent)	0.054	-0.018	0.071	-0.029
	(0.039)	(0.044)	(0.069)	(0.125)
ln (Bwd other citations / patent)	0.060***	-0.008	0.046**	0.016
	(0.013)	(0.017)	(0.023)	(0.031)
D(R&D=0)	0.108***	-0.007	-0.176	-0.326**
	(0.014)	(0.016)	(0.114)	(0.133)
NACE + Year dummies	yes	no	yes	no
Firm fixed effects	no	yes	no	yes
Observations	17,150	17,150	4,599	4,599

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the Tobin's Q defined as the stock market value over the book value of physical assets. All columns are estimated by OLS. The first two columns include a full set of year and NACE dummies while the last two columns include firm fixed effects.

Firm-level robustness checks

7 Calculating the contribution of spillovers to innovation generation

In order to compute the PatentRank spillover measure, we need to make assumption about σ_i, the contribution of spillovers in the creation of new innovations overall. Our baseline results rely on quasi innovation production function estimates from Aghion et al (2016) (Table 3). They distinguish between clean and dirty innovation. For clean the elasticity of external

Table 51: Estimation of Tobin's Q equation - Additional controls

	(1)	(2)	(3)	(4)
Dep. var.	ln Tobin's Q			
ln (R&D / assets)	0.428***	0.427***	0.132***	0.133***
	(0.030)	(0.031)	(0.038)	(0.038)
ln (Patent / R&D)	0.030	0.040	-0.021	-0.017
	(0.040)	(0.040)	(0.027)	(0.027)
ln (Fwd citations / patent)	0.054***	0.045***	0.069***	0.054***
	(0.010)	(0.011)	(0.014)	(0.015)
ln (Bwd clean citations / patent)	0.125***	0.127***	0.149**	0.152**
	(0.038)	(0.039)	(0.066)	(0.065)
ln (Bwd dirty citations / patent)	0.053	0.061*	0.038	0.042
	(0.035)	(0.035)	(0.042)	(0.042)
ln (Bwd other citations / patent)	0.067***	0.071***	0.009	0.012
	(0.011)	(0.011)	(0.014)	(0.015)
ln (family size)		0.009***		0.000
		(0.002)		(0.002)
Avg. generality of cites		-0.006		0.007
		(0.017)		(0.002)
Avg. originality of cites		-0.105***		-0.030**
		(0.017)		(0.014)
ln (PatentRank)		0.008**		0.008***
		(0.004)		(0.003)
D(R&D=0)	0.081***	0.069***	0.013	(0.013)
	(0.012)	(0.012)	(0.015)	(0.015)
NACE + Year dummies	yes	yes	no	no
Firm fixed effects	no	no	yes	yes
Observations	22,586	22,586	22,586	22,586

Notes: Robust standard errors in parentheses (* p<0.05, ** p<0.01, *** p<0.001). The dependent variable is the Tobin's Q defined as the stock market value over the book value of physical assets. All columns are estimated by OLS. The first two columns include a full set of year and NACE dummies while the last two columns include firm fixed effects.

Table 52: Estimation of Tobin's Q equation - Subsamples

	(1)	(2)	(3)	(4)
Dep. var	ln Tobin's Q			
Subsample	Granted patents only		lagged independent variables	
ln (R&D / assets)	0.406***	0.118***	0.545***	0.199***
	(0.031)	(0.040)	(0.042)	(0.027)
ln (Patent / R&D)	0.045	-0.004	0.037	-0.045
	(0.065)	(0.033)	(0.048)	(0.049)
ln (Fwd citations / patent)	0.041***	0.056***	0.052***	0.089***
	(0.010)	(0.014)	(0.011)	(0.013)
ln (Bwd clean citations / patent)	0.131***	0.194***	0.092**	-0.074
	(0.036)	(0.057)	(0.036)	(0.053)
ln (Bwd dirty citations / patent)	0.041	0.061*	0.048	-0.009
	(0.031)	(0.036)	(0.034)	(0.047)
ln (Bwd other citations / patent)	0.078***	0.026*	0.063***	-0.007
	(0.011)	(0.014)	(0.011)	(0.012)
D(R&D=0)	0.077***	0.007	0.079***	-0.006
	(0.012)	(0.015)	(0.013)	(0.019)
NACE + Year dummies	Yes	No	Yes	No
Firm fixed effects	No	Yes	No	Yes
Observations	21,072	21,077	16,906	16,908

Notes: Clustered standard errors in parentheses (* p<0.1, ** p<0.05, *** p<0.01). The dependent variable is the ln Tobin's Q defined as the stock market value over the book value of physical assets. We restrict the sample to patents applied for between 2000 and 2008. All columns are estimated by OLS and include year and NACE dummies.

knowledge stocks (i.e. spillovers) on innovative output is 0.1 and for dirty technologies 0.058. The elasticity of internal knowledge stocks on 0.445 for clean and 0.555 for dirty.

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8 Calculating the private value of innovation

Mean market value $M 2.860

Mean Asset: 3.35

Average patent over R&D: 0.014

Mean R&D stock 0.266 (for firms with R&D $>$ 0)

Coefficient of Patent over mean assets 0.101 (column 1 of table 17)

Percentage increase in market value when going from $=$ 0.101 x 1/0.266=0.38

Mean q: 1.148

New Q is 1.148*1.38=

value of patent $\$M2.86 * 0.38 = 1.58 = (Valueold + x)/Asset$

Hence $x = Asset \times 1.58 - ValueOld = 2.433$