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ABSTRACT

This paper explores the complex relationship between scientific novelty and technological impact. We measure novel science as publications which make new combinations of prior knowledge, as reflected in new combinations of journals in their references, and trace links between science and technology by scientific references in patent applications. We draw on all the Web of Science SCIE journal articles published in 2001 and all the patents in PATSTAT (October 2013 edition). We find that the small proportion of scientific publications which score on novelty, particularly the 1% highly novel scientific publications in their field, are significantly and sizably more likely to have direct technological impact than comparable non-novel publications. In addition to this superior likelihood of direct impact, novel science also has a higher probability for indirect technological impact, being more likely to be cited by other scientific publications which have technological impact. Among the set of scientific publications cited at least once by patents, there are no additional significant differences in the speed or the intensity of the technological impact between novel and non-novel scientific prior art, but the technological impact from novel science is significantly broader and reaching new technology fields previously not impacted by its scientific discipline. Novel science is also more likely to lead to patents which are themselves novel.

Keywords: Industry science links; technology transfer; scientific novelty; technological impact.

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1. Introduction

How well science and industry are interconnected and how well scientific knowledge can feed into technology development is nowadays recognized as crucial for the innovative performance, growth and competitiveness of nations (Freeman, 1987; Jaffe, 1989; Nelson, 1993). Corporations, employing more open innovation strategies, are increasingly interested in leveraging public science as an external knowledge source for their technology development (Gambardella; Cockburn & Henderson, 1996; Mansfield, 1998; Laursen & Salter, 2006; Arora et al., 2015). From the science side, universities and public research organizations have been called upon to engage more actively in knowledge transfer (Dasgupta & David, 1994; Branscomb et al., 1999; Etzkowitz & Leydesdorff, 2000).

Although the importance of science for technological innovation is widely acknowledged, the translation of science into innovation is a complex process (Bozeman, 2000; Bozeman et al., 2015). While many telling examples can be given where scientific discoveries have led to important technological breakthroughs, it is at the same time acknowledged that many good scientific ideas do not necessarily have high practical value and that the logics of scientific research and that of industrial innovation may not always be compatible (Gittelman & Kogut, 2003). Academic research still has to uncover what kinds of scientific contributions and which mechanisms and processes generate more and more effective links between science and industry.

The technology transfer literature has investigated various institutional factors that may facilitate or inhibit the success of transferring university research to industrial innovation, such as intellectual property regimes, incentives schemes, technology transfer offices, and university culture (Di Gregorio & Shane, 2003; Debackere & Veugelers, 2005; Jong, 2008; Lach & Schankerman, 2008; Geuna & Rossi, 2011). From the company side, the strategy and innovation literature has identified various mechanisms through which science contributes to company innovative performance (Cohen & Levinthal, 1990; Hicks, 1995; Cassiman & Veugelers, 2002; Fleming & Sorenson, 2004; Cassiman & Veugelers, 2006). However, neither the technology transfer nor the strategy/innovation literature has investigated the intrinsic characteristics of scientific outputs that may explain why some scientific outputs contribute disproportionately to innovation.

In this contribution, we take the science perspective of links between science and technology and aim to identify the scientific contributions which are most likely to be referenced as prior art by patented technology inventions. When looking at the characteristics of the science, we are particularly interested in novel science as prior art for patents.

Our interest in novel science resides in its special high risk/high gain characteristic. Scientific breakthroughs often require novel approaches, which at the same time, however, also face a higher level of uncertainty and potential resistance by incumbent paradigms. The combinatorial novelty perspective views novelty coming from making new combinations of preexisting components (Schumpeter, 1939; Mednick, 1962; Nelson & Winter, 1982; Simonton, 2003). Following this perspective, Wang et al. (2017) developed a measure of novelty for individual scientific publications by examining whether a publication makes first-time-ever combinations of referenced journals, taking into account the difficulty of making such new combinations. They found that novel publications, especially those that are the most novel in their field, are significantly more likely to become top cited in the long run. At the same time, however, novel publications are also more risky, as reflected in the larger dispersion in their citation distribution. Furthermore, confronted with the resistance from the incumbent paradigm, novel publications are less likely to get published in journals with high Impact Factor, and they face a delayed recognition in their citation accumulation process. In addition, the major impact of novel publications comes from other fields rather than their own.

In view of their specific high gain/high risk character and their hampered scientific recognition, it is important to study the technological impact of novel scientific publications: (a) does their novelty characteristic with its potential for high scientific impact also make them more likely sources for technological inventions? (b) do their high risk and delayed recognition characteristics observed in their scientific impact also affect their technological impact? (c) does their novel character lead to technological impact across a broader set of fields and reaching new fields of application? (d) does their novelty trait also spur more novel approaches in the technological innovations building on them?

We draw on all journal articles published in 2001 indexed in the Clarivate Analytics Web of Science (WoS) Science Citation Index Expanded (SCIE) and all patents in the EPO Worldwide Patent Statistical Database (PATSTAT) October 2013 edition. We find that novel scientific publications are significantly more likely to have technological impact than comparable non-novel publications from the same field. This higher technological impact holds particularly for those scientific publications which belong to the 1% most novel in their field. The premium in technological impact for novel scientific publications is even bigger, when correcting for their initial disadvantage of being published in lower impact factor journals. In addition to this superior likelihood of direct impact, novel science also has a higher probability for indirect technological impact, being more likely to be cited by other scientific publications which have technological impact. Conditional on having technology impact, compared with non-novel publications, novel publications do not exhibit a longer time lag to reach technological impact. More importantly, the technological impact of novel publications is broader and more unprecedented, reaching more technological fields and new fields previously not impacted by the scientific discipline of the focal scientific publication. Novel science is also significantly more likely to impact technological inventions which are themselves making new combinations of technological components, but this we only find in life sciences, not in physical sciences and engineering.

2. Science and technological impact

How science contributes to technological innovation is a long-standing research question in the innovation literature. To be able to trace the knowledge flow from science to technological innovation at a large scale, the empirical literature has been using scientific non-patent references (sNPRs), i.e., the references in patents to the scientific literature as relevant prior art for the patented inventions, following the seminal work of Narin et al. (1997).

A number of studies have examined the validity of using sNPRs for tracing knowledge flows from science to technology. In a small scale case study of nanotechnology patents, Meyer and Persson (1998) found that sNPRs may not represent a direct link between the citing patent and the cited scientific publication, but the cited scientific publication plays a more indirect role as a source of relevant background information. Tijssen et al. (2000) also noted that citations are primarily meant to indicate significant contributions of scientific research to elements of the invention. Roach and Cohen (2013), by comparing patent and survey data, found that non-patent references are a better measure of knowledge flow from public research than patent references.

Callaert et al. (2014), based on a small number of interviews of inventors, concluded that although scientific references in patents should not be interpreted as direct links between science and technology, most scientific references in patents are considered as relevant by the inventors, at least as background information for the patented invention. Similarly, Nagaoka and Yamauchi (2015), by comparing sNPRs in patents with survey results of Japanese inventors, confirmed that an sNPR does not necessarily mean that the cited scientific publication is a direct or essential input for the patented invention but rather indicates that the cited scientific publication serves as relevant background information and source of inspiration for the technological invention.

There is a large volume of empirical studies of sNPRs taking patents as the starting point and comparing the quality of the patents with and without sNPRs, where patent quality is commonly measured by the patents' forward citations. For example, Fleming and Sorenson (2004) found that patents that cite science receive more citations from other patents, but only for relatively difficult inventions, that is, those seeking to combine highly coupled components. Cassiman et al. (2008) found that referencing science does not significantly explain the forward citations of the patent, but that it is positively correlated with the scope of patents' forward citations. They also found that the linkage to science matters more at the firm level than at the invention/patent level.

In comparison, much less developed is the literature taking scientific publications as the starting point and examining which types of scientific publications are more likely to have technological impact or economic value. Prior studies taking this perspective also have used sNPRs to link science and technology. For example, Narin et al. (1997) observed a rapidly growing citation linkage between US patents and publically funded scientific publications. Similarly, Li et al. (2017) found that 30% of NIH grants generated scientific publications are subsequently cited by patents. Other studies have found that being cited by patents is a rare event for scientific publications. For example, Winnink et al. (2013) found that only 1% of their identified 15,000 intron-related WoS publications in the period 1986-2001 were cited by 1,284 (1984-2012) intron-related patents.

Ahmadpoor and Jones (2017) examined the minimum citation distance between patented inventions and prior scientific advances[1], using 4.8 million US patents and 32 million WoS research articles. They found that about 80% of cited scientific publications (i.e., cited at least once by other scientific publication) eventually link forward to a future patent, but it typically takes 2 or 3 scientific links before this technology link is established. Only 10% of cited scientific publications have a citation distance of only 1 step, i.e., being directly cited by patents. The citation distance varies by field: the fields closest to the patent frontier include nanoscience and nanotechnology, materials science and biomaterials, and computer science hardware and architecture, while mathematics is the most distant.

The speed of transfer, or the time lapse between the publication year of the cited scientific publication and the application year of the patent citing the focal scientific publication, may also differ substantially between fields of technology and is likely to be shorter in emerging fields. While Ahmadpoor and Jones (2017) found an average time lag of 6.67 years for direct citations, Finardi (2011) observed an average time lag between 3 and 4 years for nanotechnology.

In terms of what types of scientific outputs are more likely to be cited by patents, there is a high correlation between scientific impact and technological impact: scientific publications which are most cited in the scientific literature are also more likely to be cited by patents. For example, Hicks et al. (2000) showed that a US publication among the top 1% most cited publications is nine times more likely to be cited by a US patent than a randomly chosen US publication. This positive association is also confirmed by Ahmadpoor and Jones (2017) and Popp (2017).

van Raan (2017) studied the technological impact of *sleeping beauties*, i.e. scientific publications with delayed recognition. He found that *sleeping beauties* are more cited in patents than ‘normal’ publications. Inventor-author self-citations occur only in a small minority of the SB-SNPRs, but other types of inventor-author links occur quite frequently. Based on in-depth analysis of five cases of most cited sleeping beauties with sNPRs, he concluded that Sleeping Beauties SNPRs may deal with new topics, but this is not generally the case. Rather, they present new approaches within an existing topic, which pave the way to new applications. On time lags, van Raan and

[1] If a publication is directly cited by patents, then the citation distance is 1, if a publication is cited by another publication which is cited by patents, then the citation distance is 2, and so on.

Winnink (2018) found that sleeping beauties sNPRs receive their first patent citation earlier in recent years and that they are awakened increasingly earlier by a 'technological prince' rather than by a 'scientific prince.' These Sleeping Beauty findings suggest a complex connection between scientific novelty, delayed recognition, and technological impact.

3. Novel science and technological impact

In this contribution we take the science perspective of sNPRs and aim to identify which types of science are most likely to be referenced as prior art by patents. The focus of our analysis is on novel science as potential source for impacting technology inventions: is novel science more likely to be a knowledge source for technological innovation? And does the technological impact of novel science display a special profile different from that of non-novel science?

Our focus on novelty comes from its high risk/high gain nature (Foster et al., 2015; Stephan et al., 2017; Wang et al., 2017). Novel research is more likely to deliver scientific breakthroughs: pushing forward the frontier of scientific knowledge and opening the door to waves of follow-on research. However, novel research at the same times faces a higher level of uncertainty and is more likely to fail, as it explores uncharted waters. As novel research may require further development in order to fully realize its potential, it may encounter delayed impact from the relevant scientific and technological community. Impact may not only be delayed but also impeded for novel research when it disrupts, and faces resistance from, incumbent scientific or technological paradigms.

Following the combinatorial novelty perspective, novelty can be viewed as the recombination of pre-existing knowledge components in an unprecedented fashion (Schumpeter, 1939; Mednick, 1962; Nelson & Winter, 1982; Simonton, 2003). Uzzi et al. (2013) operationalized this combinatorial novelty perspective by examining the atypicality of referenced journal pairs in a scientific publication. They found that a publication which combines atypicality with conventionality is more likely to be highly cited in science. In the field of biochemistry research, Foster et al. (2015) examined pairs of chemicals and found that research introducing new combinations of chemicals is more likely to become highly cited but also displays a higher variance in their citations, confirming their high risk/high gain character. Boudreau et al. (2016)

measured the novelty of research proposals as the share of Medical Subject Headings (MeSH) pairs that are new and found that evaluators are systematically biased against novel proposals.

Wang et al. (2017) operationalized the combinatorial novelty of scientific research by examining whether a scientific publication makes new, first-time-ever, combinations of referenced journals. In addition, they weight the number of new combinations by the difficulty of doing so, where difficulty is measured by how many “common friends” the newly-paired journals have in terms of co-citations. They found that novel scientific publications have a higher variance in their scientific impact performance, confirming their high risk profile. In addition, they are less likely to be published in journals with high impact factors and have a lower chance of being a top 1% highly cited publication in the first few years after publications, showing delayed scientific impact. However, these publications have a significantly higher chance to eventually become highly cited publications in the long run. In addition, they are also more likely to have a larger indirect impact, that is, being more likely to be cited by other highly cited publications. All these findings confirm the high risk/high gain nature and delayed impact of novel science.

In view of their potential for high scientific impact, despite their higher risk and delayed impact, we ask the question whether novel scientific articles can also be expected to contribute disproportionally to new technological and industrial possibilities that build on scientific novelty. Is novel science a prime candidate for serving as a source of inspiration for technological inventions? Or does their higher risk profile make them less likely candidates as source for technological inventions? And does novel science, because of its novel high risk profile, face similar impediments in its diffusion in the technological community, like it does in the scientific community, resulting in a slower process to be picked up by the technological community, compared with non-novel science? Furthermore, in view of its high impact on follow-on scientific progress, novel science may be a source for technological inventions, indirectly, when these follow-on scientific contributions impact technology inventions. Finally, novelty in science may be a source for novelty in technology development. Novel science may be particularly relevant for impacting technological inventions in application fields which are new to its field of science or impacting technological inventions that are themselves novel in using first-time-ever combinations of technological components.

4. Data and methodology

To address our research questions we link information on scientific publications with patent information. Our unit of analysis is a scientific publication. Our publication dataset consists of all journal articles published in 2001 and indexed in the Clarivate Analytics Web of Science (WoS) Science Citation Index Expanded (SCIE), covering all natural sciences and engineering disciplines, i.e., 175 WoS subject categories indexed in SCIE. We do not consider social sciences, humanities, or arts because research in these fields are less likely to be sources for technological innovation. We exclude publications that have fewer than two references for which our novelty measure cannot be constructed. Publications with more than one subject category (up to six subject categories) are counted multiple times[2]. The final dataset has 631,624 unique publications and 982,093 observations.

We trace the technological impact of the sampled publications by citations that they receive from patents. The patent dataset we use consists of all the European Patent Office (EPO), United States Patent and Trademark Office (USPTO), and World Intellectual Property Organization (WIPO) patents in the EPO Worldwide Patent Statistical Database (PATSTAT) October 2013 edition. To link a publication to its citing patents, we match WoS publications to the non-patent-references (NPRs) listed on the front page of the patent document. It is still in discussion whether the references on the front page of the patent or the references in patent full text are a better indicator of knowledge flow from science to the patented invention (Nagaoka & Yamauchi, 2015). However, references in patent full texts are unstructured and difficult to identify. We follow the current state of art and only analyze front-page references. Specifically, we rely on a supervised machine-learning algorithm developed by Magerman et al. (2010) and Callaert et al. (2012), which (a) first classifies whether a non-patent reference is scientific (e.g., journal and conference proceeding publications) or non-scientific (e.g., news items, trade magazines, databases), with a testing accuracy rate of 92%, and (b) subsequently parses the strings of identified scientific NPRs and matches them to publication records in the WoS database.

[2] We check the robustness of our findings by (1) only analyzing publications with a single subject category or (2) reassigning publications with multiple subject categories and those in the category of "Multidisciplinary Sciences" to the majority subject category of their references.

As dependent variables for each sampled scientific publication, we consider not only its probability of having a technological impact (i.e., being cited by patents, directly or indirectly) but also a number of other characteristics of its technological impact, for example, intensity (i.e., the number of patent citations), scope (i.e., the number of citing technological fields), and being cited by novel patents. Details of dependent variables are reported in the results section.

The focal explanatory variable is scientific novelty. Following the combinatorial novelty perspective and its operationalization developed by Wang et al. (2017), we measure the novelty of a scientific publication as the number of new journal pairs in its references, weighted by the cosine similarity between the newly-paired journals.

$$Novelty = \sum\nolimits_{J_i - J_j \ pair \ is \ new} \left(1 - COS_{i,j}\right)$$

As the occurrence of novelty is highly discipline specific[3] and the distribution of the novelty measure is highly skewed[4], we use a categorical novelty variable, *NOV CAT*: (1) *non-novel*, if a publication has no new journal combinations, (2) *moderately novel*, if a publication makes at least one new combination but has a novelty score lower than the top 1% of its WoS subject category, and (3) *highly novel*, if a publication has a novelty score among the top 1% of its WoS subject category. 89% publications in our sample are in the first category, 10% in the second category. By construction, 1% of the publications are classified as highly novel, and there are no field differences in the rate of being highly novelty.

To correctly identify the association between scientific novelty and technological impact, it is important to control for other potential confounders that may influence both scientific novelty and technological impact. This holds first and foremost for the quality of the scientific publication, as the prior literature has identified that more highly cited publications are more likely to be referenced in technological inventions (Hicks et al., 2000; Ahmadpoor & Jones, 2017; Popp, 2017) and that novelty is positively related to scientific citations (Uzzi et al., 2013;

[3] The Life Sciences score relatively higher on our novelty indicator, especially Neurosciences, Pharmacology and Biology & Biochemistry. The Physical Sciences score relatively lower on novelty, especially Space Sciences and Physics.
[4] Only 11% of publications in our sample make new journal combinations.

Foster et al., 2015; Wang et al., 2017). We therefore control for the number of citations received by the focal publication from other scientific publications up till 2013.

We also control for the impact factor of the journal in which the focal publication is published. Prestigious journals are more visible and therefore may facilitate the diffusion of the scientific discovery in the technology community. At the same time, previous research has shown that novel research is less likely to be published in high impact factor journals (Wang et al., 2017), which in turn might impede the technological impact of novel science.

In addition, we control for the number of backward references of the focal scientific publication and its number of authors, which have been observed to be correlated with novelty (Uzzi et al., 2013; Lee et al., 2015; Wang et al., 2018), as well as technological impact (Popp, 2017).

We include WoS subject category dummies, so that our estimated coefficients cover within-field differences: we only compare the technological impact of novel and non-novel publications in the same scientific field but not across fields. Furthermore, we explore field heterogeneities by testing whether our findings are universal across all scientific fields or only apply for certain fields. Specifically, we distinguish between (a) life sciences and (b) physical sciences & engineering and analyze them separately.

Because of coverage biases and differences in referencing behavior across patent offices, for example, the reference list of USPTO patents is generated by both inventors and examiners and tend to be longer, while EPO patent references are only from examiners and tend to be shorter. In addition, patent citations tend to be localized, i.e., a US patent is more likely to cite US publications than European publications. To account for these systematic differences, we add three geographic dummies: whether a scientific publication has a (1) US, (2) EPO member state, or (3) Japanese affiliation. To further control for the differences in patent offices, we also check robustness of our results using only USPTO or only EPO patent data.

5. Results

5.1. Descriptive statistics

Descriptive statistics in Table 1 give some first indications that novel scientific publications, especially highly novel ones, are more likely to have a technological impact than non-novel publications. While on average about 11% of our sampled SCIE publications in 2001 are cited by patents filed up to 2013, this probability is 16% for highly novel publications (NOV CAT3) and 14% for moderately novel publications (NOV CAT2).

Insert Table 1 here

We expect that novel science is more likely to have not only a direct but also an indirect technological impact. This is confirmed by the descriptive statistics: the probabilities of being indirectly cited by patents through other scientific publications are 41% and 44% for moderately- and highly-novel publications, respectively, compared with 32% for non-novel publications.

Within the set of scientific publications that are directly cited by patents, the descriptive statistics show that, compared with non-novel publications, moderately novel publications (but not highly novel publications) receive their first patent citation earlier. Highly novel publications (but not moderately novel publications) receive more patent citations. Both moderately and highly novel publications are cited in a broader set of technological fields, are more likely to be cited in technological domains which have never cited the scientific discipline of the focal publication before, and are more likely to be cited by novel patents.

We also observe considerable differences between patent offices. When restricting to USPTO patents only, the average rate of being cited by patents is 8%, and for EPO it is only 4%. Within the set of publications being directly cited by patent, the average number of patent citations is 3.5 when restricting to USPTO patents only and 1.7 for EPO. However, the observed association between scientific novelty and various aspects of technological impact is consistent regardless of the choice of patent offices.

5.2. Direct and indirect technological impact

In the next step we run a set of econometric analyses controlling for scientific field effects and other potential confounders as described supra. First, we estimate a series of Probit models (Table 2 Column 1-4) where the dependent variable is whether a 2001 scientific publication in natural sciences and engineering is directly cited by patents filed up to 2013. Table 2 confirms a positive association between scientific novelty and direct technological impact. The positive effect of scientific novelty on direct technological impact is sizeable (Column 4): calculated at the mean level of other variables, the probability of being cited by patents is 43% higher for highly novel publications and 22% higher for moderately novel publications, compared with non-novel publications within the same field (Figure 1A).

Insert Table 2 here

Insert Figure 1 here

The results also suggest a consistently positive association between direct technological impact and scientific impact as measured by the number of scientific citations (Column 3 & 4) and journal impact factor (Column 2 & 4), in line with previous literature. More interestingly, comparing Column 2 and 4 suggests that additionally controlling for the number of scientific citations decreases the positive coefficients of novelty on direct technological impact. Scientific impact therefore mediates the positive effect of scientific novelty on technological impact. But it does so only partly, with the coefficients for novelty remaining sizable in Column 4. This suggests that the reason why novel research is more relevant and useful for technological inventions compared to non-novel research has to be found over and beyond its scientific quality.

Furthermore, comparing Column 3 and 4 suggests that additionally controlling for the journal impact factor increases the coefficients of scientific novelty on technological impact. This is reminiscent of the bias from high impact factor journals against novel science as reported in Wang et al. (2017). The comparison suggests that even for publications with the same number of scientific citations, additionally controlling for the journal impact factor (i.e., correcting the bias of higher impact factor journals against highly novel research) would increase the size of the positive novelty effect on direct technological impact, meaning that the bias in high impact factor journals against novel science hampers the technological impact of novel science. Without such bias, highly novel science would have an even greater likelihood for technological impact.

In addition, we investigate the indirect technological impact, that is, how likely are follow-on publications building on the focal original publication cited by patents. To this end, we estimate whether novel scientific publications are more likely to be cited by future publications which are themselves cited by patents. Table 2 Columns 5-8 provide consistent evidence that novel publications have a higher indirect technological impact, regardless whether controlling for the number of scientific citations or journal impact factor. Furthermore, the size of the novelty effect on indirect technological impact is also sizable but less pronounced than the novelty effect on direct technological impact. The probability of being indirectly cited by patents is 15% higher for highly novel publications and 8% higher for moderately novel publication, compared with comparable non-novel publications (Table 2 Column 8 and Figure 1B). Like for the direct technological impact, controlling for the scientific citations reduces the coefficient for novelty, while controlling for journal impact factor increases the coefficient for novelty.

5.3. Characteristics of technological impact

The observed strong positive association between scientific novelty and the existence of a direct and indirect technological impact raises the question whether, within the set of publications directly cited by patents, novel science still differs from non-novel science in the nature of its technological impact. To this end, we restrict the econometric analysis to the set of publications that are directly cited by patents and further scrutinize various aspects of their technological impact.

Insert Table 3 here

Insert Figure 2 here

We first look at the time lag. As prior literature has documented a delayed recognition for novel science in the scientific community (Wang et al., 2017), it is important to investigate whether this delayed citation/diffusion process for novel science also appears in the technological domain, that is, whether novel science needs a longer time before being picked by technological inventions, compared with comparable non-novel science. Table 3 Column 1 estimates the effect of scientific novelty on the time lag between the publication year of the scientific publication and the application year of the first patent citing the focal scientific publication. We find that the technological impact of novel science does not face a significant delay compared with non-novel publications. On the contrary, even after taking into account that highly cited and high impact factor journal publications have a shorted time lag for technological impact, novel publications take less time to receive their first patent citation than non-novel publications, but this difference is only significant for moderately novel science. The coefficient for highly novel is larger than that of moderately novel but is insignificant, because of a much smaller number of observations for highly novel publications. This finding suggests that, different from what can be observed in the scientific community, in the technology domain novel science does not face any resistant from existing paradigm nor takes a longer time to be incorporated in to follow-on R&D than comparable non-novel science.

We also assess the intensity of technological impact, that is, how many patents cite the focal scientific publication. Table 3 Column 2 and Figure 2B confirm a positive association between scientific novelty and the intensity of technological impact, which is however small and weakly significant: conditional on being cited by patents, highly novel publications receive approximately 8% patent citations than non-novel ones, while there is no significant difference between moderately- and non-novel publications.

Insert Figure 3 here

We further examine whether the technological impact of novel science reaches a larger set of technological domains. Since novel science is observed to have a more transdisciplinary scientific impact (Wang et al., 2017), we also expect a broader impact in the technology space. For one scientific publication, we measure its scope of technological impact by the number of IPC groups (at 6-digit level) of its citing patents. In addition to the complete set of controls reported before, we control for the number of patent citations, since publications cited by more patents are by chance more likely to be cited in more technological fields. There is a positive, albeit weak, association between scientific novelty and the number of patent citations. The results show that the technological impact of novel science reaches a broader set of technological fields compared with that of comparable non-novel publications. Table 3 Column 3 and Figure

3A show that, conditional on being cited by patents, highly novel publications are cited in 3% more IPC groups and moderately novel publications 1% more.

A more intriguing characteristic is the "newness" of technological impact. Is novel science more likely to have impact in technology fields which are new to its scientific discipline? We expect a positive answer to this question, as novel science introduces new approaches, which may open new areas of applications, not only for scientific research but also for technology inventions. To test this hypothesis, we examine whether a scientific publication is cited in a technological field (i.e., IPC group) which has never cited the scientific discipline (i.e., WoS subject category) of the focal publication before. Results reported in Table 3 Column 4 and Figure 3B provide strong evidence supporting this hypothesis. The premium for novel science to be cited in new technological fields is substantial: conditional on being cited by patents and compared with comparable non-novel publications, the probability of being cited in new technological fields is 52% and 20% higher for highly- and moderately-novel publications, respectively.

5.4. From novel science to novel technology

A final question we address is whether novel science is more likely to impact technology inventions that are themselves exhibiting a high level of novelty. For identifying novel patents, we follow Verhoeven et al. (2016), who characterize three types of novelty in patented inventions: (1) *Novelty in scientific knowledge origins:* A patent is identified as having novelty in scientific knowledge origins if it cites a scientific domain (i.e., WoS subject category) that has never been cited before by its technology class (i.e., IPC group at 6-digit level); (2) *Novelty in technological knowledge origins:* A patent is identified as having novelty in technological knowledge origins if it cites a technology class (i.e., IPC group) that has never been cited before by its technology class (IPC group); and (3) *Novelty in recombination:* A patent is identified as having novelty in recombination when it contains at least one pair of technology classes (i.e., IPC groups) that were previously unconnected.

Insert Figure 4 here

Econometric results reported in Table 3 Columns 5-7 and correspondingly Figure 4A-C confirm a positive relationship between scientific novelty and all three types of technological novelty.

First, novel publications display a sizeable advantage over comparable non-novel publications in being cited by patents with novelty in scientific knowledge origins: highly novel publications have a 27% higher chance of being cited by patents with novelty in scientific origins, and moderately novel publications a 17% higher chance (Table 3 Column 5 and Figure 4A). This result confirms the previous results regarding the newness of technological impact (Table 3 Column 4 and Figure 3B). Second, highly- and moderately-novel publications are 12% and 6% respectively more likely than comparable non-novel publications to be cited by patents with novelty in technological knowledge origins (Table 3 Column 6 and Figure 4B). This premium for novel science is significant but less pronounced than the premium of being cited by patents with novel scientific knowledge origin. Finally, highly- and moderately-novel publications are respectively 21% and 15% more likely to be cited by patents with novelty in recombination, compared with non-novel publications, *ceteris paribus*. These effects are very sizable. The results therefore confirm that novel science is particularly significant in impacting technology inventions which themselves have novel recombination features.

5.5. Scientific field heterogeneity

As we can expect important differences between scientific disciplines in how research is conducted and how scientific knowledge feeds into technological innovation, we include in the econometric analysis controls for scientific field (i.e., WoS subject categories dummies). We thus account for field differences in the likelihood and nature of being cited by patents. In other words, we estimate and test whether and how novel papers are more likely to be cited by patents compared with non-novel papers in the same field. To further test whether the reported relationships between scientific novelty and technological impact are field-specific, we run the analyses separately for (1) life sciences (including medical sciences) and (2) physical sciences & engineering. Results are reported in Table 4 and 5.[5]

Although our main result on a higher direct technological impact for novel science is robust in both subsamples, we do observe some interesting field differences. First, while moderately novel

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[5] We obtained similar results when further (a) distinguishing between medical sciences (more applied part) and the rest within life science and (b) distinguishing between computer sciences & engineering and the rest in physical sciences and engineering. These results are not reported and are available upon request from the authors.

papers have a higher indirect technological impact than non-novel publications in both life sciences and physical sciences & engineering, highly novel publications appear to have a higher indirect technological impact only in physical sciences & engineering but not in life sciences. This finding is consistent with a shorter distance between scientific research and technological inventions in life sciences, as also found in Ahmadpoor and Jones (2017). Second, novel publications have a broader technological impact reaching more technological domains than non-novel publications, only in physical sciences & engineering but not in life sciences. Third, novel publications are more likely to be cited by novel patents in life sciences but not in physical sciences & engineering.

Insert Table 4 here

Insert Table 5 here

5.6. Robustness tests

We run a series of further robustness tests (details available upon request from the authors). For studying the scope and newness of the technological impact (Table 3 Columns 3 and 4), we operationalize the technological field by IPC subclasses at the 4 digit rather than the 6 digit level. Results are robust with the novelty effects even more pronounced.

All our econometric analyses include geographic dummies to account for the differences between patent offices. We additionally test the robustness of our findings by replicating all analyses using (1) USPTO patents only and (2) EPO patents only. All results are robust in both subsamples, except that (a) the weakly positive effect of scientific novelty on the number of patent citations in the total sample become insignificant in both subsamples; (b) the positive effect of scientific novelty on the number of citing IPC groups become insignificant when using USPTO patents only; and (c) the positive effects of scientific novelty on being cited by patents with novel technological knowledge origins and on being cited by patents with novel recombination become insignificant when using EPO patents only.

The dataset consists of 631,624 unique publications and 982,093 observations, where publications with multiple WoS subject categories are counted multiple times. We tested two alternative approaches: (1) excluding publications with multiple subject categories from the analysis and (2) reassigning papers with multiple subject categories and papers in the category of "Multidisciplinary Sciences" to the majority subject category of their references. Our main results on the higher likelihood of direct and indirect technological impact for scientific novelty remain, as the results on no time lag and the new pathways for technological impact. The size and direction of the results on the number of citing classes and the likelihood to impact combinatorial novel patents are similar, but loose significance for the highly novel publications.

In addition, basic and applied research might have different propensities of being cited by patents. This might bias our results, to the extent that basicness is correlated with the novelty measure and insufficiently captured by our field fixed effects. To address this concern, we additionally control for the basicness level, using the CHI journal classification scheme (Noma, 1986; Hamilton, 2003), for the subset of publication covered in this classification scheme. All our findings are robust.

6. Conclusion

This paper adds to our understanding of the interplay between science and technology, by taking the science perspective of industry science links and examining what types of science is most likely to have a technological impact, in particular, whether novel science is more likely to have a technological impact and displays a distinct impact profile compared with non-novel science.

Drawing on all the WoS SCIE journal articles published in 2001 and all the patents in PATSTAT (October 2013 edition), we examine the relationship between scientific novelty and technological impact, tracing technological impact of individual scientific publications through their citations in patents. We find that a handful of scientific publications which score on novelty (about 11%) are significantly more likely to have a technological impact, in particular the top 1% highly novel scientific publications in their field. The technological impact premium of novel science is sizeable: the probability of being cited by patents is 43% higher for highly novel publications than comparable non-novel publications in the same field, and 22% higher for moderately novel publications. The technological impact premium for novel scientific publications remains substantial even when we control for their higher scientific impact, suggesting that the superior technological impact of novel publications arises from factors beyond their high scientific quality and value. The technological impact premium for novel publications is even bigger when correcting for their disadvantage of being less likely to be published in high impact factor journals. Without such bias, novel publications would have a greater technological impact.

In addition to their superior direct technological impact, novel publications also have a higher indirect technological impact, being more likely to be cited by other scientific publications which are cited by patents. The probability of being indirectly cited by a patent is 15% higher for highly novel publications and 8% higher for moderately novel publications than comparable non-novel publications.

Within the set of scientific publications that are directly cited by patents, novel publications do not display a significantly longer delay in technological impact, unlike in the scientific community, where their impact was found to be significantly delayed. Conditional on being cited by patents, there is no consistent evidence that novel publications are cited more often than comparable non-novel publications. However, novel publications do have a broader technological impact, covering more diverse technological fields. More importantly, novel publications stand out because of the unprecedented nature of their technology impact, i.e., reaching technology fields previously not impacted by the scientific fields of the novel publications. In addition, novel publications are more likely to be cited by patents which themselves show a high level of novelty. Although the observed effects all control for field effects and although our main result on a higher direct technological impact for novel science is robust across fields, there are nevertheless some interesting differences between scientific disciplines. For example, while novel publications are more likely to be cited by patents both directly and indirectly in physical sciences & engineering, in life sciences there is only a significant direct impact, consistent with a shorter distance between scientific research and technological development.

These findings speak to the policy push for more active technology transfer. Science, as a self-governed system of work organization, is structured to encourage novel contributions to the common stock of scientific knowledge (Merton, 1973; Whitley, 1984; Stephan, 1996). Our findings show that novel science also has a higher, broader, and unprecedented technological impact, suggesting that the pursuit of scientific novelty does not conflict with the policy goal of higher economic value.

At the same time, these results also contribute to the discussion in science policy that funding agencies and their expert panels are increasingly risk-averse, favoring relatively safe projects at the expense of more risky projects that explore new and untested approaches (Boudreau et al., 2016; Stephan et al., 2017; Wang et al., 2018). The concern in these discussions is that being too risk-averse harms the long-term progress of science, as novelty is an important source of scientific breakthrough advancing the scientific frontier. This paper provides evidence for further reasons to support (or not bias against) novel science, namely because of its greater technological impact. As there is an increasing pressure on science to be economically and socially relevant, our findings suggest that scientific novelty should be encouraged (or at least not discouraged) not only for the sake of scientific progress but also for its greater contribution to technological development. Any bias in the current science system against novelty, will not only imperil scientific progress but also hinder and delay technological development. As not only novel publications themselves are significant knowledge sources for technology, but also their follow-on publications, improving the visibility and recognition of novel scientific research within the scientific community will facilitate the diffusion and utilization of scientific knowledge in the technology domain. A particular pathway that should be cleared is any bias by higher impact factor journals for novel publications, as these not only delay scientific recognition for novel research, but also significantly impede technological impact.

In order to better understand industry science links, we need more studies uncovering intrinsic characteristics of science that are particularly useful for technological innovation. Other characteristics of science beyond its novelty need to be investigated, such as its interdisciplinary nature, its basicness, or whether it is starting a new emerging field. Considering the important differences between scientific disciplines (e.g., how research is conducted, how novelty is generated, and how scientific knowledge feeds into technology), it is important to do more in-depth studies within specific scientific disciplines to gain a better understanding of the relationship between scientific novelty and technological impact. In addition, the characteristics of the technologies that use novel science should be further examined. Future research should also explore how the pathway from novel science to technological inventions unfolds differently from that of non-novel science. Does a successful translation of novel science require a shorter cognitive, geographic, or social distance compared to non-novel science? Are inventor-author links more critical for translating novelty science into technology? Does novel science require more shared understandings, stronger social ties and shorter network distances to be successfully translated to technology? Is geographic proximity more important when translating novel science to technology? These are but a few of the interesting further research questions brought about by this paper.

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Table 1. Descriptive statistics.

		ALL	NOV CAT1	NOV CAT2	NOV CAT3
1	# publications	982,093	871,753	100,600	9,740
2	% publications cited by patent	10.66%	10.24%	13.75%	16.28%
3	% publications cited by patent (USPTO)	8.01%	7.71%	10.20%	12.72%
4	% publications cited by patent (EPO)	4.46%	4.24%	6.16%	6.52%
5	% publications indirectly cited by patent	32.62%	31.54%	40.82%	44.30%
6	% publications indirectly cited by patent (USPTO)	24.82%	24.03%	30.69%	35.29%
7	% publications indirectly cited by patent (EPO)	20.64%	19.80%	27.06%	29.90%
8	# publications cited by patent	104,728	89,311	13,831	1,586
9	Average years of time lag in technological impact	3.37	3.38	3.35	3.38
10	Average number of patent citations	3.92	3.92	3.88	4.36
11	Average number of citing IPC groups (6-digit level)	7.19	7.10	7.65	8.03
12	% publications cited in new IPC group (6-digit level)	10.09%	9.85%	11.12%	15.08%
13	% publications cited by novel patents in recombination	8.11%	8.00%	8.44%	11.14%
14	% publications cited by novel patents in technological origin	26.16%	26.06%	26.21%	31.70%
15	% publications cited by novel patents in scientific origin	15.02%	14.69%	16.53%	20.56%

Statistics for the number of 2001 publications, % publications cited by patents, and % publications indirectly cited by patents (through other publications), that is, row 1-7, are based on all journal articles in Web of Science-Science Citation Index Expanded (SCIE), while all the other statistics are based on the subset of these publications which are cited by patent. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

Table 2. Direct and indirect technological impact.

	Directly cited by patents Probit				Indirectly cited by patents Probit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NOV CAT2	0.092***	0.125***	0.093***	0.105***	0.052***	0.097***	0.046***	0.062***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
NOV CAT3	0.171***	0.237***	0.169***	0.192***	0.088***	0.189***	0.081***	0.116***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.014)	(0.014)	(0.015)	(0.015)
JIF (ln)		0.491***		0.163***		0.841***		0.293***
		(0.004)		(0.005)		(0.004)		(0.004)
Scientific			0.355***	0.328***			0.664***	0.622***
citations (ln)			(0.002)	(0.002)			(0.002)	(0.002)
Pubs	630697	630697	589667	589667	631617	631617	590556	590556
Obs	981081	981081	921193	921193	982081	982081	922141	922141
Pseudo R2	0.113	0.135	0.172	0.174	0.168	0.216	0.316	0.320

*** p<.001, ** p<.01, * p<.05, + p<.10. Control variables (the number of authors (ln), whether internationally coauthored, the number of references (ln), whether have US affiliations, whether have EPO member state affiliations, whether have Japanese affiliations, and WoS subject category dummies) are incorporated in all regressions but not reported. Robust standard errors in parentheses. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

Table 3. Characteristics of technological impact.

	(1) Years of time lag OLS	(2) # citing patents Poisson	(3) # citing IPC6s Poisson	(4) Cited in new IPC6 Probit	(5) Cited by novel patents (sci) Probit	(6) Cited by novel patents (tech) Probit	(7) Cited by novel patents (comb) Probit
NOV CAT2	-0.082**	0.009	0.012+	0.098***	0.095***	0.041**	0.070***
	(0.026)	(0.017)	(0.007)	(0.017)	(0.016)	(0.014)	(0.019)
NOV CAT3	-0.105	0.079+	0.031+	0.228***	0.148***	0.086*	0.096*
	(0.071)	(0.044)	(0.017)	(0.043)	(0.040)	(0.038)	(0.049)
JIF (ln)	-0.259***	-0.001	0.016**	-0.265***	-0.113***	-0.098***	-0.095***
	(0.020)	(0.019)	(0.005)	(0.014)	(0.012)	(0.011)	(0.015)
Scientific citations (ln)	-0.082***	0.321***	0.045***	0.035***	0.055***	0.040***	0.074***
	(0.008)	(0.013)	(0.002)	(0.006)	(0.005)	(0.005)	(0.006)
Patent citations (ln)			0.594***	0.383***	0.481***	0.664***	0.461***
			(0.003)	(0.007)	(0.006)	(0.006)	(0.007)
Pubs	63726	63726	63667	63663	60893	60893	60838
Obs	103378	103378	103289	103282	98752	98757	98668
(Pseudo) R2	0.036	0.093	0.364	0.157	0.133	0.180	0.157

*** p<.001, ** p<.01, * p<.05, + p<.10. Control variables (the number of authors (ln), whether internationally coauthored, the number of references (ln), whether have US affiliations, whether have EPO member state affiliations, whether have Japanese affiliations, and WoS subject category dummies) are incorporated in all regressions but not reported. Robust standard errors in parentheses. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

Table 4. Life sciences

	(1) Directly cited by patents Probit	(2) Indirectly cited by patents Probit	(3) Years of time lag OLS	(4) # citing patents Poisson	(5) # citing IPC6s Poisson	(6) Cited in new IPC6 Probit	(7) Cited by novel patents (sci) Probit	(8) Cited by novel patents (tech) Probit	(9) Cited by novel patents (comb) Probit
NOV CAT2	0.091***	0.021**	-0.102**	0.016	-0.003	0.104***	0.099***	0.054**	0.065**
	(0.007)	(0.006)	(0.030)	(0.020)	(0.008)	(0.022)	(0.019)	(0.017)	(0.024)
NOV CAT3	0.158***	-0.016	-0.022	0.085	-0.007	0.209**	0.216***	0.161**	0.104
	(0.023)	(0.021)	(0.097)	(0.053)	(0.023)	(0.063)	(0.055)	(0.051)	(0.072)
JIF (ln)	0.166***	0.326***	-0.232***	0.045*	0.028***	-0.220***	-0.107***	-0.108***	-0.133***
	(0.006)	(0.005)	(0.024)	(0.021)	(0.006)	(0.018)	(0.016)	(0.014)	(0.020)
Scientific citations (ln)	0.315***	0.628***	-0.042***	0.289***	0.030***	0.028**	0.039***	0.025***	0.052***
	(0.003)	(0.003)	(0.012)	(0.018)	(0.003)	(0.008)	(0.007)	(0.007)	(0.009)
Patent citations (ln)					0.579***	0.371***	0.477***	0.671***	0.453***
					(0.004)	(0.009)	(0.008)	(0.008)	(0.010)
Obs	487715	488488	62955	62955	62905	62902	60009	60009	59992
(Pseudo) R2	0.154	0.314	0.026	0.067	0.324	0.131	0.113	0.160	0.120

*** p<.001, ** p<.01, * p<.05, + p<.10. Control variables (the number of authors (ln), whether internationally coauthored, the number of references (ln), whether have US affiliations, whether have EPO member state affiliations, whether have Japanese affiliations, and WoS subject category dummies) are incorporated in all regressions but not reported. Robust standard errors in parentheses. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

Table 5. Physical sciences & engineering

	(1) Directly cited by patents Probit	(2) Indirectly cited by patents Probit	(3) Years of time lag OLS	(4) # citing patents Poisson	(5) # citing IPC6s Poisson	(6) Cited in new IPC6 Probit	(7) Cited by novel patents (sci) Probit	(8) Cited by novel patents (tech) Probit	(9) Cited by novel patents (comb) Probit
NOV CAT2	0.126***	0.134***	-0.049	0.037	0.047***	0.072**	0.088**	0.017	0.023
	(0.011)	(0.009)	(0.045)	(0.028)	(0.013)	(0.028)	(0.026)	(0.024)	(0.030)
NOV CAT3	0.237***	0.268***	-0.197+	0.057	0.063*	0.255***	0.049	0.003	0.062
	(0.026)	(0.023)	(0.101)	(0.066)	(0.026)	(0.058)	(0.056)	(0.054)	(0.064)
JIF (ln)	0.181***	0.213***	-0.438***	-0.089*	0.004	-0.323***	-0.097***	-0.045*	-0.037
	(0.009)	(0.008)	(0.036)	(0.036)	(0.011)	(0.024)	(0.022)	(0.020)	(0.024)
Scientific citations (ln)	0.344***	0.629***	-0.114***	0.297***	0.062***	0.036***	0.064***	0.052***	0.085***
	(0.003)	(0.003)	(0.012)	(0.013)	(0.003)	(0.007)	(0.007)	(0.007)	(0.008)
Patent citations (ln)					0.621***	0.390***	0.482***	0.655***	0.464***
					(0.005)	(0.009)	(0.009)	(0.009)	(0.010)
Obs	434511	434527	42307	42307	42269	42267	40554	40563	40501
(Pseudo) R2	0.196	0.301	0.048	0.089	0.401	0.144	0.125	0.163	0.136

*** p<.001, ** p<.01, * p<.05, + p<.10. Control variables (the number of authors (ln), whether internationally coauthored, the number of references (ln), whether have US affiliations, whether have EPO member state affiliations, whether have Japanese affiliations, and WoS subject category dummies) are incorporated in all regressions but not reported. Robust standard errors in parentheses. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

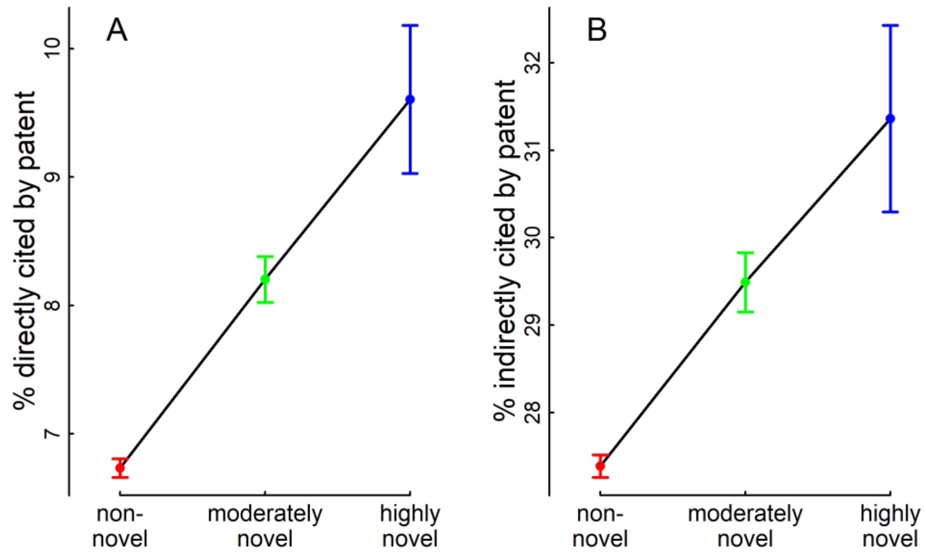

Figure 1. Novel publications are more likely to be cited by patents, directly and indirectly. **(A)** estimated probability of being directly cited by patents, based on the regression reported in Table 2 column 4. **(B)** estimated probability of being indirectly cited by patents, through another publication, based on the regression reported in Table 2 column 8. Estimated values are for an average paper (i.e., taking all other independent variables at their means) in different novel classes. The vertical bars represent the 95% confidence interval. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

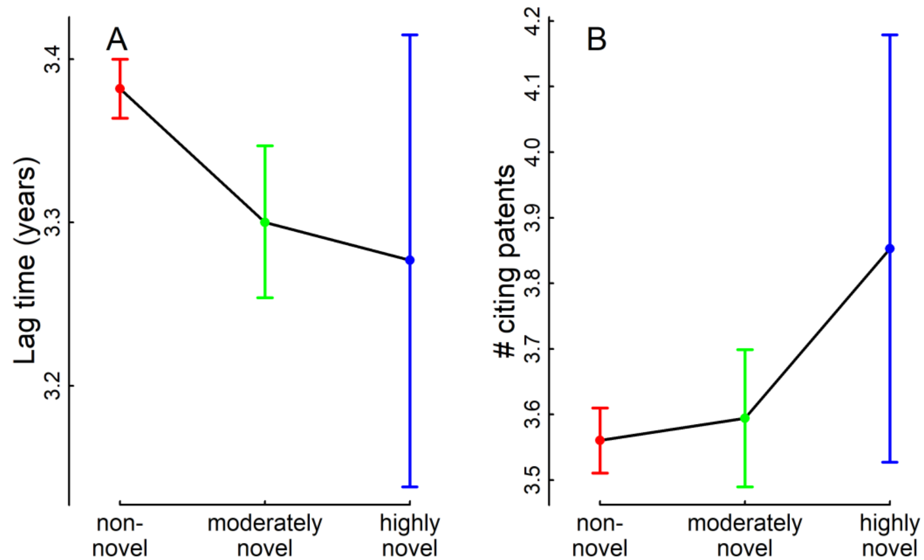

Figure 2. There are no significant differences in the speed or the intensity of patent citations between novel and non-novel publications. (A) estimated time lag between publication year and application year of the first patent citing the focal publication, based on Table 3 column 1. **(B)** estimated number of patent citations (or the number of citing patents), based on the regression reported in Table 3 column 2. Estimated values are for an average paper (i.e., taking all other independent variables at their means) in different novel classes. The vertical bars represent the 95% confidence interval. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

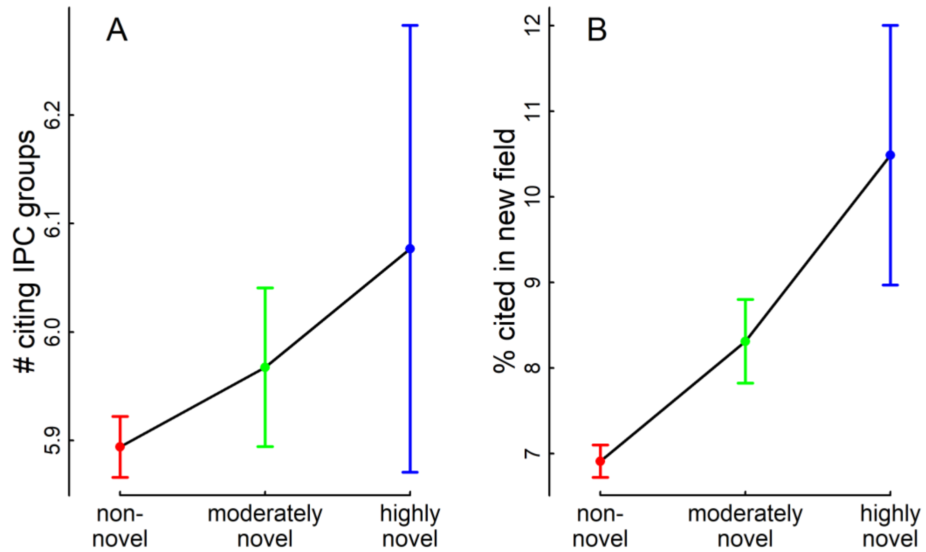

Figure 3. The technological impact from novel science is significantly broader and reaching new technology fields previously non-impacted by its scientific discipline. (A) estimated number of IPC groups (6-digit level) in which the focal publication is cited, based on the regression reported in Table 3 column 3. **(B)** estimated probability of being cited in IPC groups which has never referenced the WoS subject category of the focal publication before, based on the regression reported in Table 3 column 4. Estimated values are for an average paper (i.e., taking all other independent variables at their means) in different novel classes. The vertical bars represent the 95% confidence interval. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).

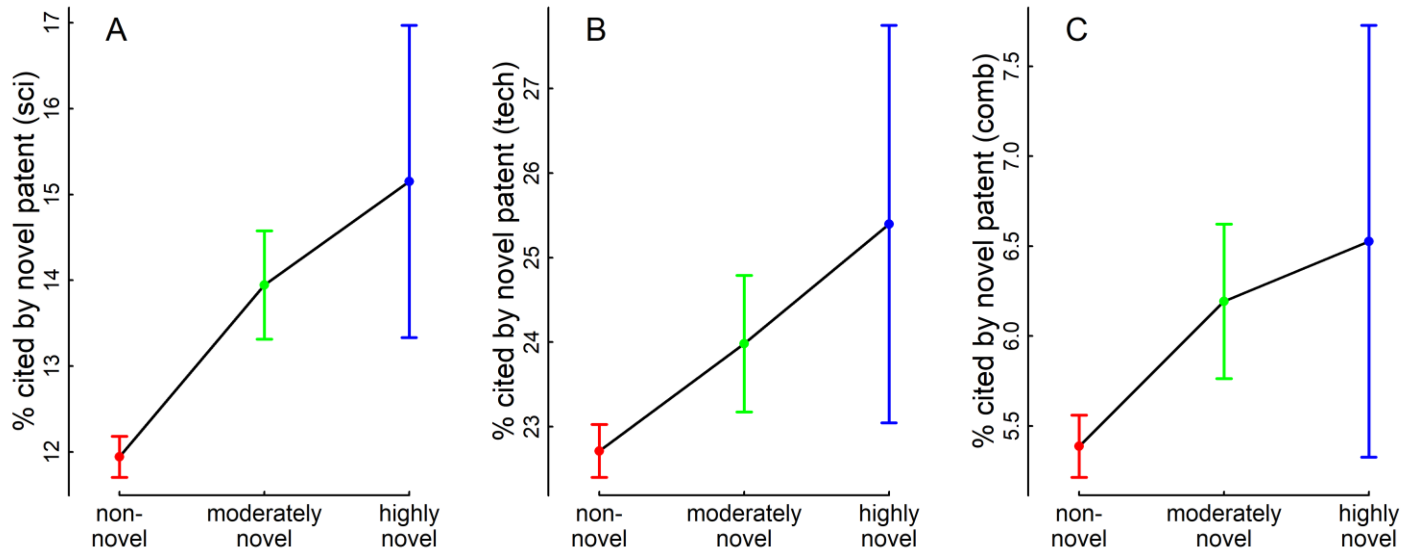

Figure 4. Novel publications are more likely to lead to novel patents. (A)-(C) estimated probability of being cited by novel patents with new scientific knowledge origin, new technological knowledge origins, and new recombination, based on the regression reported in Table 3 column 5-7, respectively. Estimated values are for an average paper (i.e., taking all other independent variables at their means) in different novel classes. The vertical bars represent the 95% confidence interval. Data sourced from Clarivate Analytics Web of Science Core Collection and EPO Worldwide Patent Statistical Database (October 2013 edition).