The Relevance of Scientific Knowledge Externalities for Technological Change and Resulting Inventions Across European Metropolitan Areas

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Contrary to perceptions in which technological development proceeds independently of scientific research, the interplay between science and technology has been recognized as an essential part in technological change, industrial competitiveness, and economic growth. While the process of knowledge exchanges between the nexus is conceptually well grounded in relevant literatures, the absence of quantitative measures and assessments of such linkages may underestimate the importance of scientific knowledge inputs for generating high-impact innovative outcomes. In this regard, we propose a large quantitative analysis on knowledge externalities from science to technology by investigating patent citations to science data across European metropolitan regions. First, we construct a dataset of patent citations to scientific knowledge that includes information on the spatial origins of knowledge spillovers. Subsequently, the ratio of internal scientific knowledge sourcing to external sources and its effect on patent citation impact is evaluated. Findings suggest that regions with a higher reliance on their internal scientific resources tend to generate inventions with higher technological impact, and that a strong connection between science and technology is even more effective in advanced industrial regions.

Keywords: Knowledge externalities and spillovers, Scientific knowledge , Technological knowledge, Patent citation to science, Innovation impact, European metropolitan regions

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Introduction

Contrary to perceptions in which technological development proceeds independently of scientific research (Cohen et al., 2002), interconnection between science and technology has been recognized as an essential part in technological change, industrial competitiveness, and economic growth (Fagerberg, 2003; Nelson, 1993). Scientific and technological spheres differ in the way of disclosure of knowledge and reward systems, i.e., scientists aim for pure research and publications, and inventors focus on economically useful knowledge and patents, thus operate based on different kinds of objectives, decision making rules, interpretation, etc. There is no direct overlap between the two systems, however, there is interaction between them (Kaufmann & Tödtling, 2001). Scientific knowledge generated at universities and research institutes provides a fundamental understanding for practical applications and contributes to technological advancements (Ahmadpoor & Jones, 2017). In other words, industrial innovation is conceived as a cumulative process of basic to applied research and then to development and commercialization to the patented ends. For instance, one of the key functions driving innovative dynamics in Silicon Valley is the knowledge exchange between high quality research-based science from universities and inventive efforts made in firms and industries (Hoppmann, 2021). Given that scientific research is a key to initiating new innovative outputs, it is worthwhile to investigate the proceeding from scientific knowledge to ultimate technological applications.

In this regard, scholars have a longstanding interest in revealing and disentangling the connection between science and industry complex. Discourses in this regard have taken place in the science, technology, and innovation (STI) policy literature, in which innovation processes are viewed as a linear sequence of stages including scientific research, development and commercialization that lead to economic benefits (Jensen et al., 2007), and the innovation systems literature that emphasizes the interplay between institutional functions; here mainly focusing on science and industry linkages, in diverse geographical scales (Cooke et al., 1997; Lundvall, 1992; Malerba, 2002). Based on these discussions, policy makers have aimed to build closer relationships between scientific bodies and industries to encourage knowledge transfer from basic research to practice. Moreover, several attempts were made to design and assess the contribution of academic research to technological developments by applying indicators such as research and development (R&D) expenditures, number of publications, and number of patents to measure the efficiency of such knowledge flows (Godin, 2009; Hall & Jaffe, 2018). However, these measurements are not sufficient to capture how knowledge 'flows' from scientific research activities to patented inventions (Alhusen et al., 2021).

One particular way to trace knowledge spillovers is to conduct a patent citation analysis (Jaffe et al., 1993). Patents leave a trail of knowledge flows from prior art documents with detailed information such as addresses of inventors, which allows us to track what kind of knowledge was exchanged or how knowledge flowed from place to place. Since we are interested in the knowledge exchange between science and technology, we can refer to patent citations to the non-patent literature (NPL), e.g., research publications. Patent citations to publications represent technological development drawn from the pool of research results, which is basically showing the extent of an academic contribution (Kim et al., 2022). Recently, empirical assessments have emerged to quantify the connection between science and technology using this citation information. For instance, Jefferson et al. (2018) showed that there has been a dramatic increase in translating scholarly activities to patented outcomes, and studies (e.g. Ahmadpoor & Jones, 2017; Poege et al., 2019;

Wang & Li, 2018) argue that the value of a patent is highly contingent to its involvement of science and that the relationship is fundamentally driven by the science quality thereof. In other words, more and more new inventions are relying on scientific knowledge, and it turns out that those inventions are likely to be more impactful than patents which do not have scientific bases, and that high-quality science is frequently selected and linked to further practical applications.

Technological advancements rely on scientific knowledge development; however, despite this potential important consequence of co-development, we currently lack insights into how its dynamics occur in terms of geographical features, e.g., if countries and regions pool their own scientific resources or retrieve those developed elsewhere, and whether the dynamics actually induce benefits such as technological impact. For the former, first, it is likely that regions would exploit their internal scientific sources if they already possess relevant knowledge, because it significantly reduces time and cost of searching, acquiring, assimilating, and using external knowledge (Tödtling & Auer, 2021). Further, empirical studies have found that knowledge spillovers between publications and patented inventions are geographically localized (Belenzon & Schankerman, 2013; Heinisch et al., 2016), as it was evidenced by citation analyses between patents in the past (Jaffe et al., 1993; Thompson, 2006; Thompson & Fox-Kean, 2005). Furthermore, findings also indicate that a scientific portfolio is somewhat related to fields of subsequent technological development (Balland & Boschma, 2022; Catalán et al., 2020; Van Looy et al., 2006). Based on these insights, we can assume that regions that have considered the importance of co-evolution of science and technology will have higher reliance on their internal research outputs. Then, we should assess whether the attempt to co-develop science and technology leads to higher technological competences and then encourage countries and regions to invest in both knowledge production domains. Murmann (2013), for instance, claimed that the co-development of academic research and industry have led certain countries to attain a comparative advantage over others in particular fields. Knowledge exchanges within co-evolution set-ups have mutually reinforcing effects in both science and industry (Hoppmann, 2021). Likewise, studies taking a co-evolutionary perspective can offer new insights into the dynamics of technological change.

Consequently, this paper aims to explore and evaluate the spillover patterns from science to technology and its impact in shaping technological capabilities of regions. In detail, we measure the degree of internal scientific knowledge exploitation in regional economies and estimate its effect on technological impact on those respective regions. To do so, we use patent citations to science data projected onto our focal spatial units, i.e. European metropolitan areas. Knowledge diffusion is then traced via geographical extensions observed in patent documents, and our principal interest in the present paper relates to geographical traces of knowledge spillovers from research publications to patents, which we expect to be localized if regions had placed efforts to support both knowledge spheres. This study aims to significantly enhance our understanding of the science-technology nexus and resulting dynamics in technological change. To the best of our knowledge, the present investigation is one of the first studies that examines the co-development process of science and technology via a large-scale quantitative approach for Europe and thus should deliver highly relevant insights for STI policy making.

To convert on the objectives, initially a concordance table of global patent – NPL citations based on Marx and Fuegi (2020) is dveloped, and subsequently rrelevant patent information from the European Patent Office (EPO) PATSTAT database and publication information from the Microsoft Academic Graph (MAG) database are integrated in order to link the various data sources (Kedron et al., 2020). Then all documents were geocoded to the European NUTS3 regional level classifications based on the residency or affiliation information of associated inventors and authors. Following these steps it was possible to create the final dataset that contains patent-NPL linkages and associated regional information. Further, the location information was used to aggregate the data into metropolitan regions. The scope are patents developed in metro-regions in Europe (EU15 + Switzerland & Norway) between the period of 2000 and 2017. Finally, utilizing relevant variables and indicators, we conducted empirical analyses to investigate the relationship between the share of internal knowledge sourcing and technological impact. Our findings indicate that regions with higher dependence on local scientific resources tend to have higher technological impact than others with lower reliance. The tendency gets clearer in highly industrialized regions, which shows the important role of scientific knowledge and the connection between science and technology in shaping regional knowledge capabilities.

The reminder of the paper is organized as follows. In the next section, some of the relevant literature is presented and discussed, which allows us to derive at our main research questions. This is followed by a section that outlines the data, variables, and models that are employed in the analyses. Lastly, an overview of results and then a further discussion and concluding remarks are provided.

The Science and Technology Nexus and its Impact on Technological Change

The underlying perception in the innovation process and its contribution to economic benefits is that innovation is comprised of a sequence of distinct stages of different kinds of knowledge production activities, i.e., basic scientific research, applied research, development, and commercialization, that altogether may lead to economic gains (Flink & Kaldewey, 2018; Grupp & Mogee, 2004). The first two parts are done by scientific bodies, mostly resulting in publications, and the two latter stages refer to technological activities that are then mostly protected via intellectual property rights, e.g., patents. The idea of the assortment of distinct series of actions in innovation processes, the so-called a linear model, led to the introduction of an STI mode of innovation, in which learning starts from searching for new knowledge of scientific principles, recombines knowledge to achieve technological development, and results in new products or processes (Jensen et al., 2007). Namely, technologies involve supporting knowledge derived from fields of science. New scientific knowledge generated by research serves as an input for innovative inventions and inherent to the mode is the exchange and spillovers of knowledge between science and technology. The procedure can take place within a firm or industry, but also by interactions with actors outside the firm such as research institutions (Malerba, 1992). The STI mode therefore is used to advice policymakers on how and where to implement supplementary tools to foster innovation and support interactions of diverse centers of new knowledge production such as universities and institutions that create scientific knowledge and firms that exploit those knowledge components to deliver innovations (Fitjar & Rodríguez-Pose, 2013).

In the STI mode of innovation, scientific research often does not directly affect technological development, i.e., research does not result in inventions with immediate industrial applications, but rather in indirect way through documented results in a codified form (Cohen et al., 2002). Despite the fact that the linear model remains prevalent in STI policies (Flink & Kaldewey, 2018), only recently has this feature of linear relationship between advance understanding and practical applications been quantified in a few studies that examined patent citations to science to demonstrate knowledge flows between academia and industry. For instance, Ahmadpoor and Jones (2017) and Wang and Li (2018) showed that patents that refer to scientific publications have higher citation impact than the other patents that do not refer to NPLs as their prior art. Those studies confirmed that more and more patents are linking back to scientific knowledge base and that scientific knowledge has significant contribution to technological activities. At the same time, Poege et al. (2019) found strong positive selection of high-quality scientific works into NPL references, showing connectivity between the bodies of patented inventions and research publications.

The connection between science and technology further became recognized as a mutual interplay beyond the linear process. Scholars have started to acknowledge the interactive nature of science and technology and have employed a co-evolutionary perspective to explore how interfaces between science and industry shape an entity's overall capabilities over time (Fagerberg, 2003; Kaufmann & Tödtling, 2001), and it has been proposed as a theoretical framework to back up interdependent dynamics embedded in technological change (Nelson, 1993). For instance, it is widely accepted that science – industry linkages played a crucial role in innovative clusters such as Silicon Valley (Hoppmann, 2021), and lack of such interactions would weaken the effectiveness of national research capabilities and the emergence of new technologies (Alhusen et al., 2021; Goldstein & Narayanamurti, 2018). In line with this argument, 'systems of innovation' literature has long been interested in the interplay between the two groups of bodies at various geographic and sectoral scales (Cooke et al., 1997; Lundvall, 1992; Malerba, 2002). Especially in national innovation systems (NIS), Lundvall (1992) emphasized the elements including firms, universities, and research institutes and their relationships in production, diffusion, and use of new and economically useful knowledge. Here, the way knowledge is distributed and used among those main elements' interactions is central to the performance of an innovation system (Godin, 2009). Thus, in this approach, scientific research first constitutes a fundamental component within the system since the co-evolutionary process of knowledge development is based on the overall state of knowledge in scientific disciplines and the level of technological capabilities. Then knowledge transfer from science to technology occurs through diverse channels such as collaborative research and migration of researchers from public to private sectors. Moreover, firms often access the results of scientific research in codified forms such as publications and patents. Consequently, knowledge production and spillovers from universities and research institutes are increasingly the focus of policy makers to maximize the societal impact of innovations (Blankenberg & Buenstorf, 2016).

Given the importance of science and technology nexus in the process of technological change, it is not surprising that relevant literature has long been interested in how to design and evaluate the interfaces between the two groups (Cohen et al., 2002). Empirically, measures to assess the STI mode of innovation and NIS include input measures such as R&D expenditures or personnel and output indicators such as publications and patents, which are then compared and used to reflect efficiency level (Godin, 2009; Hall & Jaffe, 2018). However, approach to capture the 'flow' of knowledge between science and technology is not well understood (Alhusen et al., 2021). Indicators should be able to consider the use of such knowledge – producing, diffusing, and exploiting economically useful knowledge. A few attempts have been made to consider the co-evolutionary process of science and technology, e.g., Wong and Wang (2015) used the quantity of publications and patents at national level to assess the patterns of cumulative knowledge production of science and technology and examined the relationship between the proportion of science-based patents and citation impact, both at national level, to evaluate the impact of science-based knowledge usage on technological change in emerging countries. Further, Blankenberg and Buenstorf (2016) showed a mutually reinforcing effect in the evolutionary process by employing the number of patents, publications, and etc. in German laser industry. These attempts have contributed to empirically explain a systematic perspective in innovation process, however, are still limited to investigating superficial bond of science and technology since the measurements cannot reveal the diffusion process nor exploitation of scientific knowledge in technological advancements.

In short, while the process of knowledge exchange between science and technology is conceptually well grounded in the STI and NIS literatures, etc., absence of quantitative measures and assessments of such phenomenon may underestimate the importance of science in patenting activities. In this regard, we propose a large quantitative analysis on knowledge externalities from science to technology based on patent citations to science information. Backward citations in patent documents are treated as a proxy of the ability to identify the value of external novel information and exploit it to the end, and references indicate useful knowledge that are selected for creation of new knowledge (Cohen & Levinthal, 1990). Consequently, patents' NPL references show to which extent technological knowledge involves academic contribution (Kim et al., 2022). In this sense, we believe that using patent citations to science information is acceptable to achieve our research aim to evaluate the patterns of science and technology links and their impact on technological change. Some studies have used this kind of data to disclose some features of knowledge spillovers from scientific knowledge to patented inventions in terms of geographical extent. For instance, Belenzon and Schankerman (2013) showed that the knowledge spillovers from university publications to patents in the US are strongly localized and sensitive to distance. Heinisch et al. (2016) also confirmed international geographical localization in patent – NPL citations in Dutch context. These studies prove that the inherent nature of 'stickiness' in knowledge (Von Hippel, 1994) applies to both scientific and technological knowledge. Furthermore, some recent studies found that regions tend to develop new technology that is related to their scientific portfolio, and regions with strong scientific base are highly likely to become technological frontiers in the same domain while regions with only technological capabilities often downgraded to one of the followers (Balland & Boschma, 2022; Catalán et al., 2020).

Given that knowledge is innately sticky to specific places, there is overlap between scientific and technological bases, and science matters in technological development, we can assume that regions who possess scientific knowledge base in relevant industrial fields are likely to refer to their internal scientific sources since there is no need to spend time and effort to search, assimilate, and exploit external scientific knowledge to develop their technological capabilities. In other words, regions that count more on internal scientific resources rather than external sources are likely to have strong connection between science and technology or are likely to put efforts on promoting both research and inventing sides, which in turn should lead to better performance in technological activities as argued in the STI and NIS literatures. Subsequently, based on all the discussions above, our hypothesis is: *regions with higher reliance on internal scientific research bases are likely to have higher technological impact*. If we can accept this hypothesis, we can argue that technological advancements stem from scientific base and provide relevant implications for the STI policies.

Data and Methods

As shown in Fig 1, the projection of patent citations to science on the European metropolitan regions are as follows. First, we retrieved a concordance table of patents and their references to scientific publications from the work of Marx and Fuegi (2020). It provides a publicly available patent – publication link records by linking global patents and their NPL citations based on MAG database. Using this as a reference, we extracted relevant patent information including priority year, citations, inventor addresses, etc. from the EPO PATSTAT and publication information including publication year, institution addresses, etc. from the MAG database. Then we geocoded addresses with NUTS3 regional level classifications in all the documents. Further, those that can be assigned to metropolitan regions were aggregated to metro-regional level classifications.

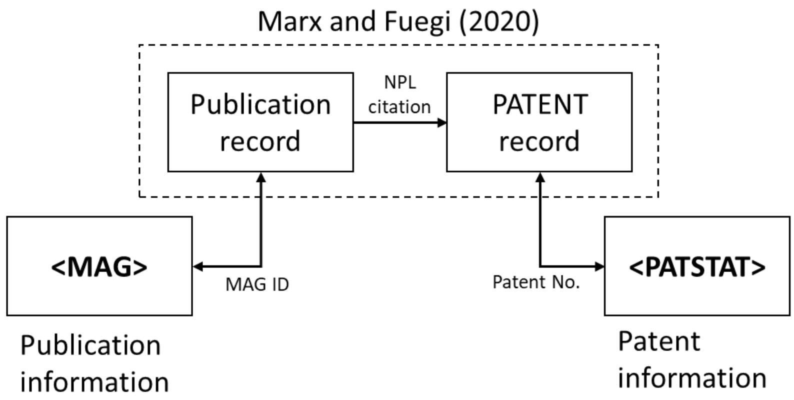

Figure 1. Data overview

Following these steps created our own dataset of patent citations to science with the list of metropolitan regions and NUTS3 regions entailed in the process of knowledge production in science and technology. We limited our sample to patents developed from metropolitan regions in EU15 + Switzerland & Norway covering from 2000 to 2017. Our final dataset for the analysis contains information from 218 metro-regions from 17 countries (See Appendix A for the geographic profile). Regional level knowledge and economic indicators from Web of Science (calculated by authors), Cambridge Econometrics, and Eurostat are also added. Table 1 describes the variables included in our analysis.

Table 1. Description of variables

Variable		Definition	Data source
$FwdCit_{r,t}$	Technological impact	Number of 5-year forward citations in region *r* in year *t*	EPO PATSTAT
$IntraShare_{r,t}$	Degree of internal science sourcing	Ratio of *intra* to *inter* dummies in region *r* in year *t*	MAG, EPO PATSTAT
$KCapAbs_{r,t}$	Technological absorptive capacity	Number of backward citations of patents in region *r* in year *t*	EPO PATSTAT
$KCapPat_{r,t}$	Technological output	Number of patent applications in region *r* in year *t*	EPO PATSTAT
$KCapSci_{r,t}$	Scientific output	Number of scientific publications in region *r* in year *t*	Web of Science
$KCapIns_{r,t}$	Scientific research activities	Number of research institutions in region *r* in year *t*	Web of Science
$KCapSciQ_{r,t}$	Quality of scientific knowledge	Number of forward citations of publications in region *r* in year *t*	MAG
$UnivPat_{r,t}$	Sci-Tech activities	Share of university patents in region *r* in year *t*	EPO PATSTAT
$CitLag_{r,t}$	Sci-Tech citation lag	Average citation lag year between publications and patents in *r* in *t*	MAG, EPO PATSTAT
$PopDen_{r,t}$	Region size	Population density (population/area) in region *r* in year *t*	Cambridge Econometrics, Eurostat

* r – metropolitan regions (Eurostat), t – 2000~2017

$FwdCit_{r,t}$ is the dependent variable measuring technological impact of a region *r* at time *t* which is calculated by the number of 5-year forward citations. Forward citation index has been exploited in many previous studies to reflect impact or value of a patent (Ahmadpoor & Jones, 2017; Jefferson et al., 2018; Poege et al., 2019), and therefore we also utilize the number of forward citations.

$IntraShare_{r,t}$, the independent variable, concerns the degree to which regions source internal scientific knowledge compared to external resources. Here, whether it is internal or not is identified by national boundaries. For example, if a patent from Paris refers to scientific literature published from France, we classified the case as intra-sourcing; otherwise, inter-sourcing. According to previous literature, geographical localization of knowledge is significantly observed within national boundaries rather than regional boundaries (Thompson, 2006; Thompson & Fox-Kean, 2005), because knowledge carrying individuals such as inventors relocate frequently within a country but not across international borders. In this sense, national borders are considered to distinguish internal and external knowledge. Following this rationale, based on the information of the list of incorporated regions in each patent – NPL link, if there is at least one matched region between publication and patent, we assign the patent as 1 for *intra dummy*; otherwise, 0. At the same time, if regions do not match, we assign the patent as 1 for *inter dummy*; otherwise, 0. Examples are illustrated in Table 2.

Table 2. Illustration of intra and inter dummies for the $IntraShare_{r,t}$ variable

	NPL(s)	**Patent**	***Intra dummy***	***Inter dummy***
Case 1	Paris	Paris	1	0
Case 2	Paris	London, Berlin	0	1
Case 3	Paris	Paris, Berlin	1	1

Then, we sum up the values of intra and inter dummies at each regional level, respectively, and compare the values to calculate the $IntraShare_{r,t}$:

$$IntraShare_{r,t} = \frac{\sum_i^r intra\ dummy_{i,t}}{\sum_i^r inter\ dummy_{i,t}}$$

where *i* stands for each patent, *r* for each metro-regions, and *t* for year.

All the other variables are included to control knowledge capacities and size of region *r* in year *t*. First, $KCapAbs_{r,t}$ is for technological absorptive capacity measured by the number of backward citations (Cohen & Levinthal, 1990; Harhoff et al., 2003; Kim et al., 2022), and $KCapPat_{r,t}$ stands for technological output measured by the number of patent applications (Van Looy et al., 2006; Wang & Li, 2018). Next, science relevant capacities include: $KCapSci_{r,t}$ for scientific output measured by the number of publications (Balland & Boschma, 2022; Van Looy et al., 2006); $KCapIns_{r,t}$ for scientific research activities measured by the number of research institutions (Feldman, 1994; Leten et al., 2014) including universities, etc.; and $KCapSciQ_{r,t}$ for the quality of scientific knowledge measured by the number of forward citations received by publications (Wang & Li, 2018). For variables $KCapSci_{r,t}$ and $KCapIns_{r,t}$, we used the Web of Science database and counted the number of publications the number of institutions that appear on the list of authors' affiliation information for each NUTS2 level regions. Furthermore, we tried to take account of science – technology link support or places where universities are actively pursuing patented knowledge by including $UnivPat_{r,t}$, the share of university patents (Heinisch et al., 2016), and the effect of referencing the most disruptive scientific documents that are likely to be cited for a long time by $CitLag_{r,t}$, the average citation lag between publications and patents (Poege et al., 2019). With these variables should we able to control the effects of universities' active participation in patenting and the effects of sourcing the most disruptive or more established scientific knowledge that are likely to be old. Lastly, $PopDen_{r,t}$ is included to control the size of regions (Colombelli, 2016).

With the variables in hand, we conducted negative binomial regressions following that our dependent variable is the count of citations. Also, as we observed high skewness in our variables except for $CitLag_{r,t}$ and $PopDen_{r,t}$, we log-transformed the variables for the regression. Furthermore, given that the patterns of patent citations to science may vary depending on industrial profile of regions – knowledge intensive regions have larger number of collaborations between academy and industry for knowledge creation from research to commercialization (McKelvey et al., 2003; Moodysson, 2008), while regions with low technological capabilities have little demand for local scientific knowledge (Lehmann & Menter, 2016; Rodríguez-Pose, 2001) –, we attempted to extract sub-samples of regions with high industry employment (25% quantile among the dataset) where they are likely to be active in technological development and of regions with low industry employment (below 75% quantile among the dataset) where there are likely to be little demand for research and development. Scientific research is more likely to be used in more applied sciences or engineering fields, and those used in industrial inventions tend to be relatively mature (Cohen et al., 2002). Finally, we again split our sample into two time dimensions, 2000~2007 and 2008~2017, to investigate whether results change over time.

Summary statistics and correlations of the variables are appended to Appendices B and C. According to the statistics, the average ratio of internal scientific knowledge sourcing to external sourcing is about 0.3 in the European metro-regions, which can be interpreted as: there are many regions that only develop technological knowledge in certain fields instead of nurturing basic research capabilities as well and thus should pool scientific references from outside for developing respective technological competences. Moreover, we find high correlation values between $\ln KCapAbs_{r,t}$ & $\ln KCapPat_{r,t}$, $\ln KCapSci_{r,t}$ & $\ln KCapIns_{r,t}$, and $\ln UnivPat_{r,t}$ & $\ln KCapPat_{r,t}$, which is expected; however, later in the analysis stage we find that there are no multicollinearity biases affecting our regression model.

Results

Regression results are represented in Table 3. First of all, Model (1) shows that the $IntraShare_{r,t}$ variable has positive and significant effect on patent forward citation: regions with higher share of internal scientific knowledge have higher citation impact. In other words, the results confirm that technological impact and sourcing scientific knowledge developed within the same country are positively related. Assuming that citations between patents and research articles are likely to occur within the same field, we suppose that regions with high technological capabilities possess high level of scientific knowledge in the same domain as well. This finding also indicates that regions that hold competitiveness in both science and technology can accomplish higher technological advancements, which stresses the importance of scientific foundation for developing technological capabilities. Moreover, knowledge capacity variables have positive and significant effects on technological impact except for $\ln KCapIns_{r,t}$ and $lnUnivPat_{r,t}$. As we observe significant role of publishing activities, $\ln KCapSci_{r,t}$ and $\ln KCapSciQ_{r,t}$ – mostly the outcomes from universities and research institutions –, on patent impact but no significant effects of the pool of research institutions and university patenting, we can assume that research institutions and universities support enhancing technological impact in an indirect way.

To examine the differences in the relationship between technological impact and internal sourcing of science capitals depending on the degree of regional knowledge intensity, we divided our sample into regions with high and low industrial employment. Models (2) and (3) measure the effects of variables in high industrial regions, top 25% regions, and low industrial regions, low 25% regions, respectively. To line up the regions according to their level of industrial activities, we used industry employment data of regions and calculated the average industry employment level of all the regions in our dataset throughout the whole period. We then identified regions that are included in the top and low 25% quantiles. According to the results in Models (2) and (3), a clear division between the two groups of regions can be found: the $IntraShare_{r,t}$ coefficient is higher in knowledge intensive-industrial regions than that of low-industrialized regions. Regions that are more focusing on manufacturing industries which are likely to be more active in patenting inventions show much higher effect in the reliance on their scientific resources rather-than external sources. This finding strongly supports our argument that regions with high technological capabilities rely on their own scientific knowledge assets, highlighting that technological advancements cannot be achieved without investments in science.

Lastly, we compared the results by splitting time periods into 2000~2008 and 2009~2017 to seek whether the results change over time. The findings suggest that the relevance of local scientific sources to technology have significantly increased in the later years. This tendency is also confirmed when we tried splitting time dimensions into three periods (2000-2005, 2006-2011, 2012-2017), etc. We can presume that as regions continue to specialize in specific knowledge domains, they have put effort to strengthen their capabilities in both scientific research and technological improvements, which came to be fertile conditions for technological progress.

Table 3. Regression results

Model (DV)	**(1) NB ($FwdCit_{r,t}$)**	**(2) NB Industry Emp. Top 25% ($FwdCit_{r,t}$)**	**(3) NB Industry Emp. Low 25% ($FwdCit_{r,t}$)**	**(4) NB Year <=2008 ($FwdCit_{r,t}$)**	**(5) NB Year >2008 ($FwdCit_{r,t}$)**
$IntraShare_{r,t}$	.3910***	.4437***	.3400**	.1091	.3723***
	(.0565)	(.1181)	(.1327)	(.0661)	(.0765)
ln$KCapAbs_{r,t}$	.4139***	.3907***	.4470***	.8995***	.4756***
	(.0126)	(.0185)	(.0342)	(.0298)	(.0192)
ln$KCapPat_{r,t}$	.6080***	.6262***	.6726***	.1394***	.5451***
	(.0185)	(.0276)	(.0514)	(.0318)	(.0272)
ln$KCapSci_{r,t}$	.0812***	.1189***	.1303***	-.0156	-.0037
	(.0127)	(.0225)	(.0262)	(.0152)	(.0207)
ln$KCapIns_{r,t}$	.0017	-.0042	.0013	.0405***	.0683***
	(.0126)	(.0191)	(.0318)	(.0133)	(.0230)
ln$KCapSciQ_{r,t}$	.0276**	.0337	-.0076	-.0020	.0269
	(.0111)	(.0205)	(.0232)	(.0130)	(.0149)
ln$UnivPat_{r,t}$	-.0193	-.0042	-.0552	-.0158	-.0467***
	(.0116)	(.0170)	(.0325)	(.0134)	(.0153)
$CitLag_{r,t}$	.0557***	.1023***	.0266**	.0200***	.0379***
	(.0048)	(.0086)	(.0104)	(.0068)	(.0058)
$PopDen_{r,t}$	.0507***	.0475	.0172	-.0329	.0379***
	(.0173)	(.0249)	(.0382)	(.0189)	(.0058)
Constant	-2.1783***	-2.9544***	-2.3589***	-.5967***	-1.4228***
	(.0887)	(.1732)	(.2443)	(.1581)	(.1416)
N	1,828	598	343	893	935
R-square	.2221	.2086	.2372	.2557	.2296

***, **, and * indicate significance at 1, 5, and 10%, respectively.

Discussion and Concluding Remarks

To investigate the importance of science and technology linkage in technological innovations, this study aimed to analyze the effect of internal scientific knowledge sourcing on technological impact of the European metro-regions. We assumed that countries and regions where they focus on developing both scientific and technological knowledge spheres are likely to refer to their own scientific research outputs rather than external resources due to the inherent nature of spatial localization of knowledge (Jaffe et al., 1993; Von Hippel, 1994) and the relatedness between scientific base fields and subsequent technological entries (Balland & Boschma, 2022; Catalán et al., 2020). Based on this assumption, we constructed a dataset of patent citations to science with the location information of showing geographical trail of knowledge spillovers from science to technology. Then, we compared the degree of internal scientific knowledge sourcing to external scientific knowledge sourcing for each region and assessed its impact on patent citations from the region. Our results show that regions with higher reliance on their own scientific sources tend to have higher technological impact, and the strong connection between science and technology is even more effective in advanced industrial regions. These findings suggest that technological advancements cannot be achieved without the investment in science.

Contrary to the conceptions in which scientific progress and technological development operate in independent domains, we find significant role of scientific bases in technological progress. Basic research activities may be regarded as less important in patented inventions since there is substantial uncertainty about potential fields of application from 'basic' research (Blankenberg & Buenstorf, 2016), however, recent empirical approaches have confirmed that there is an increase in patents' reliance on knowledge developed from scholarly activities and the level of academic contribution matters in patents value (Ahmadpoor & Jones, 2017; Jefferson et al., 2018; Poege et al., 2019). Our analysis in this paper further investigated direct knowledge flows from science to technology empirically, showing how science matters in technological development and how regions source and develop their capabilities based on both domains of knowledge. This can provide some STI policy implications: it strengthens the rational of regional association that cut across science – technology divide or public – private divide. From the perspective of regional STI policy makers, our analysis indicates that fostering ties to national universities and research institutes is worthwhile activity when fostering industrial progress. That is, countries and regions should invest in basic science and promote more closed coupled science and industry linkages to speed up and enhance technological progress.

Overall, this study contributes by providing a large quantitative analysis on regional-level pattern of scientific knowledge spillovers to technology and its impact on technological influence based on patent – NPL citation analysis. This approach is novel in that it provides further insights into the path of knowledge creation and wider perspectives on the elements of regional knowledge which were often limited to patent landscape. This paper also emphasizes the interplay across science – technology which subsequently magnifies the importance of investment in basic research and establishment of science – industry linkages. Consequently, we believe there is a great potential of research questions to be answered using the patent citations to science data in diverse themes and geographical scales, and our research is just one of the first attempts to understand the dynamics of knowledge development. Since there are limits in which this single study can cover, future studies can explore further on various patterns and benefits of regions' knowledge production, diffusion, and use of knowledge within the science and technology nexus, e.g., which one, regional specialization or diversification influences regions' capacities to source from their scientific bases and the impact of their patents or whether diversity of scientific knowledge producing actors affects patenting outputs. Also, using geographical distances rather than binary border-in/out variable may help us to understand better on the trace of knowledge spillovers from science to technology.

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Appendix

Appendix A. Geographic profile of the dataset

Country	Number of metropolitan regions
Austria (AT)	5
Belgium (BE)	5
Switzerland (CH)	5
Germany (DE)	65
Denmark (DK)	4
Greece (EL)	2
Spain (ES)	19
Finland (FI)	3
France (FR)	33
Ireland (IE)	2
Italy (IT)	21
Luxemburg (LU)	1
Netherlands (NL)	9
Norway (NO)	2
Portugal (PT)	3
Sweden (SE)	4
United Kingdom (UK)	35
Total	**218**

Appendix A. Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
$FwdCit_{r,t}$	3,395	102.7708	241.1201	0	2,844
$FwdCit_{3,r,t}$	3,395	77.4633	186.2926	0	2,474
$IntraShare_{r,t}$	3,355	.2920	.2507	0	3
$KCapAbs_{r,t}$	3,395	73.5193	171.5863	0	1,868
$KCapPat_{r,t}$	3,395	424.7714	838.5168	1	7,290
$KCapSci_{r,t}$	3,395	2,431.7540	4,927.8570	1	76,135
$KCapIns_{r,t}$	3,395	185.2919	480.4829	1	10,057
$KCapSciQ_{r,t}$	3,359	223.2969	390.5231	0	8,958.2
$UnivPat_{r,t}$	3,391	2.5533	9.2488	0	400
$CitLag_{r,t}$	3,395	7.3731	3.2039	0	52
$PopDen_{r,t}$	3,327	.5885	.8369	.0315	8.9218

Appendix B. Correlation table

	Variable	1	2	3	4	5	6	7	8	9
1	$FwdCit_{r,t}$									
2	$IntraShare_{r,t}$	.0699								
3	$\ln KCapAbs_{r,t}$	.6690	.0684							
4	$\ln KCapPat_{r,t}$	.6924	.0774	.8297						
5	$\ln KCapSci_{r,t}$	.3057	-.0887	.3084	.3957					
6	$\ln KCapIns_{r,t}$	.2747	-.0531	.1995	.4057	.7022				
7	$\ln KCapSciQ_{r,t}$	.1902	.0544	.3475	.3242	.2752	.2017			
8	$\ln UnivPat_{r,t}$	-.4285	-.0019	-.5554	-.6210	.0568	-.0463	-.1135		
9	$CitLag_{r,t}$	.0646	-.0455	-.0819	.0203	.0378	.0606	.0045	-.0312	
10	$PopDen_{r,t}$	.0853	-.2339	.0009	.0384	.1347	.1077	.0117	-.0365	.0381