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# Three Essays on Regional Expertise Alignment and Inventive Performance

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# THESE DE DOCTORAT

Trois essais sur l'alignement de l'expertise  
régionale et la performance inventive

**Tan Tran Thai**

GREDEG

**Présentée en vue de l'obtention  
du grade de docteur en** Sciences de gestion  
d'Université Côte d'Azur

**Dirigée par :** Nathalie Richebe (*HDR*)

**Co-encadrée par :** Ludovic Dibiaggio (*non  
HDR*)

**Soutenue le :** 29 Mai, 2020

**Devant le jury, composé de :**

Ron Boschma, Professeur, Utrecht University  
Francesco Castellaneta, Professeur, Skema  
Business School

Maryann Feldman, Professeure, University of  
North Carolina

Jerome Vicente, Professeur, University of  
Toulouse



# DOCTORAL THESIS

## Three Essays on Regional Expertise Alignment and Inventive Performance

**Tan Tran Thai**

GREDEG

**Defense presented for the purpose of  
obtaining a PhD** in Management Sciences  
Of Université Côte d'Azur  
**Thesis director** : Nathalie Richebe (*HDR*)  
**Co-director** : Ludovic Dibiaggio (*non HDR*)  
**Soutenu le** : 29th May, 2020

**Devant le jury, composé de :**  
Ron Boschma, Professor, Utrecht University  
Francesco Castellaneta, Professor, Skema  
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North Carolina  
Jerome Vicente, Professor, University of  
Toulouse

**Titre**

Trois essais sur l'alignement de l'expertise régionale et la performance inventive

**Title**

Three Essays on Regional Expertise Alignment and Inventive Performance

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## **Titre**

Trois essais sur l'alignement de l'expertise régionale et la performance inventive

## **Résumé**

Cette thèse traite de la manière dont l'expertise des régions en matière de connaissances affecte les performances d'innovation dans la région et contribue à la littérature sur les systèmes régionaux d'innovation.

Le premier chapitre s'appuie sur la littérature des systèmes régionaux d'innovation qui souligne le rôle de la proximité spatiale sur les activités innovantes locales. Au sein de la structure régionale, deux sous-systèmes interconnectés sont bien étudiés par les chercheurs : la génération de connaissances et l'exploitation des connaissances. Je mets en doute les mesures traditionnelles et souligne les limites des études actuelles. Je mets en évidence la dynamique des sous-systèmes de connaissance régionaux ainsi que leurs relations relatives. Je suggère en outre de nouvelles mesures de ces sous-systèmes de connaissance aux couches les plus fines (c'est-à-dire les différents types d'expertise en science et technologie) en utilisant un ensemble de données unique de brevets et de publications scientifiques français (1990-2015), puis j'examine leurs relations avec les dépenses régionales de R&D. Les résultats montrent que les dépenses de R&D ont une relation positive avec le nombre de compétences scientifiques et technologiques de la région, mais pas avec le niveau de ces compétences. Je montre également que le niveau d'expertise technologique augmentera s'il est complémentaire à une science spécifique.

Le deuxième essai traite de la valeur temporelle de l'expertise scientifique locale. Dans cette étude, nous étendons particulièrement la littérature bien connue sur la diffusion des connaissances localisées. Nous soutenons que l'expertise scientifique locale, étroitement liée à l'industrie locale, renforce la capacité des inventeurs proches à reconnaître, accéder et acquérir les matériaux scientifiques potentiels, en particulier les publications scientifiques, qui favorisent leurs activités d'innovation. Par conséquent, cela contribue à réduire le temps que les inventeurs locaux passent à se référer à des publications scientifiques, et donc à augmenter la valeur de l'invention. Nous mesurons le délai entre l'année de publication des publications citées et la citation du brevet pour saisir la diffusion rapide des connaissances de la publication scientifique à l'invention. Les valeurs de l'innovation focale sont saisies par le décompte des citations directes et multigénérationnelles. Le document peut aider le chercheur à mieux comprendre les différents mécanismes de diffusion des connaissances et/ou l'interaction entre la science, l'innovation et le progrès technologique.

Le troisième essai se concentre sur la région en tant que source critique pour les inventeurs/entreprises locaux en leur fournissant des capacités d'innovation plus élevées. Nous développons en particulier le concept d'alignement régional en répondant sur la plateforme régionale des systèmes de connaissance. Nous sommes d'avis que, dans le cadre de la production de connaissances, les inventeurs combinent différents éléments de connaissances pour créer une invention. Au cours du processus de recherche, les inventeurs sont confrontés à différents obstacles et risques. Nous soutenons que l'alignement régional comme l'efficacité des plates-formes de connaissances, qui reflète les synergies potentielles entre les connaissances complémentaires et hétérogènes, l'expertise, les compétences et les acteurs locaux. Ces synergies facilitent l'apprentissage interactif, augmentant ainsi les capacités d'absorption des acteurs locaux. Par

conséquent, l'alignement régional peut atténuer le risque et l'incertitude de la création de connaissances. Ces résultats montrent que l'alignement régional offre aux acteurs locaux des capacités exploratoires plus élevées pour rechercher et évaluer les connaissances distantes, ce qui contribue à réduire la variance et à augmenter l'utilité de leurs innovations exploratoires.

**Mots-clés:** géographie de l'innovation, alignement régional, science, diffusion des connaissances, progrès technologique, plate-forme

## **Title**

Three Essays on Regional Expertise Alignment and Inventive Performance

## **Abstract**

This dissertation deals with how regions' knowledge expertise affects the innovative performance in the region and contributes to the literature of regional innovation systems.

The first chapter relies on the literature of regional innovation systems that underlines the role of spatial proximity on local innovative activities. Within the regional structure, two interconnected subsystems are well studied by scholars recently the knowledge-generation and the knowledge exploitation. I question traditional measurements and point out the limitations of current studies. I highlight the dynamics of regional knowledge subsystems as well as their relative relationships. I further suggest the new measurements of these knowledge subsystems at the finer-grained layers (i.e. different types of expertise in science and technology) by using a unique dataset of French patents and scientific publications (1990-2015), then examine their relationships with regional R&D expenditure. The results show that R&D expenditure has a positive relationship with the numbers of the scientific and technological expertise of the region; however, not to the level of expertise. I also show that the level of technological expertise will increase if it is complementary to a specific science.

The second essay deals with the time value of local scientific expertise. In this study, we particularly extend the well-known literature of localized knowledge diffusion. We argue that local scientific expertise closely aligned with local industry enhances the ability of proximate inventors to recognize, access and acquire the potential scientific materials, particularly scientific

publications, that favour for their innovation activities. As a result, it helps to reduce the time for local inventors to reference to scientific publications, hence increase the value of the invention. We measure the time lag between the published year of cited publications and citing patent to captures the fast diffusion of knowledge from scientific publication to the invention. The values of the focal innovation is captured by the direct and the multi-generational forward citation counts. The paper may help the scholar to better understand the different mechanisms for the diffusion of knowledge and/or interplay between science, innovation and technological progress.

The third essay focuses on the region as a critical source for local inventors/firms by providing them with higher innovative capacities. We particularly elaborate on the concept of regional alignment by replying on the regional platform of knowledge systems. We take the view of knowledge generation that inventors combine different elements of knowledge to create an invention. During search process, inventors face different barriers and risks. We argue that the regional alignment as the effectiveness of knowledge platforms, which reflects potential synergies between complementary and heterogeneous knowledge expertise, competences and local actors. These synergies facilitate interactive learning, thus increase absorptive capacities to local actors. As a result, regional alignment may mitigate the risk and uncertainty of knowledge creation. These results show that regional alignment provides local actors with higher explorative capabilities to search and evaluate the distant knowledge, which helps to reduce variance and increase the usefulness of their explorative innovations.

**Keywords:** geography of innovation, regional alignment, science, diffusion of knowledge, technological progress, platform

# Table of Contents

<b>LIST OF FIGURES.....</b>	<b>11</b>
<b>LIST OF TABLES .....</b>	<b>12</b>
<b>ACKNOWLEDGEMENTS.....</b>	<b>13</b>
<b>INTRODUCTION .....</b>	<b>13</b>
<b>CHAPTER 1.....</b>	<b>26</b>
<b>R&amp;D AND KNOWLEDGE EXPERTISE OF FRENCH REGIONS .....</b>	<b>26</b>
ABSTRACT .....	27
INTRODUCTION .....	28
THE THEORETICAL CONCEPT OF REGIONAL KNOWLEDGE EXPERTISE .....	33
<i>The different types of regional knowledge expertise .....</i>	<i>33</i>
<i>The dynamic relationships between science and technology.....</i>	<i>35</i>
METHODOLOGY FOR MEASURING KNOWLEDGE EXPERTISE .....	37
<i>Units of analysis and indicators.....</i>	<i>37</i>
<i>Data collection.....</i>	<i>40</i>
<i>Measuring variables .....</i>	<i>45</i>
EMPIRICAL ANALYSIS AND RESULTS FOR FRENCH REGIONS .....	48

<i>Regional scientific expertise</i> .....	48
<i>Regional technological expertise</i> .....	56
<i>The interdependence between different types of science and technology at the national level</i> .....	63
DISCUSSION AND CONCLUSION .....	68
<b>CHAPTER 2</b> .....	<b>70</b>
<b>THE TIME VALUE OF LOCAL SCIENTIFIC EXPERTISE</b> .....	<b>70</b>
<b>THE TIME VALUE OF LOCAL SCIENTIFIC EXPERTISE</b> .....	<b>71</b>
ABSTRACT .....	71
INTRODUCTION .....	72
LITERATURE .....	76
<i>The diffusion of knowledge in geographical proximity or distance</i> .....	76
<i>Scientific expertise and the rapid diffusion of knowledge across science and technology</i> .....	78
<i>Scientific expertise and the rate of the diffusion of knowledge across technologies</i> .....	80
DATA AND RESEARCH METHODS .....	80
<i>Data and sample selection</i> .....	80
<i>Method and Measurement:</i> .....	83
RESULTS .....	95

DISCUSSION AND CONCLUSION .....	100
<b>CHAPTER 3.....</b>	<b>104</b>
<b>REGIONAL ALIGNMENT AND INNOVATIVE PERFORMANCE OF REGIONS.....</b>	<b>104</b>
ABSTRACT .....	105
INTRODUCTION .....	106
LITERATURE.....	110
<i>Search for new knowledge .....</i>	<i>110</i>
<i>Regional alignment as a platform.....</i>	<i>113</i>
<i>Regional alignment and innovation performance.....</i>	<i>116</i>
<i>Regional alignment and explorative performance.....</i>	<i>121</i>
DATA AND RESEARCH METHODS .....	122
<i>Data and sample selection .....</i>	<i>122</i>
KEY VARIABLES.....	126
<i>Dependent variable .....</i>	<i>126</i>
<i>Independent variables .....</i>	<i>127</i>
<i>Model specification.....</i>	<i>132</i>
RESULTS .....	134

DISCUSSION AND CONCLUSION .....	140
<b>CONCLUSION .....</b>	<b>144</b>
ANSWERS TO THE RESEARCH QUESTIONS .....	144
MAIN CONTRIBUTIONS .....	146
LIMITATIONS .....	153
MOTIVATING NEW RESEARCH .....	154
<b>BIBLIOGRAPHY.....</b>	<b>157</b>
<b>APPENDIX 1 .....</b>	<b>169</b>

## List of Figures

Figure 1. 1: The distribution of the difference in years between the priority year and the published year of a patent .....	41
Figure 1. 2: French patents from 1990 to 2015 in PATSTAT patent data (Autumn version 2015) .....	43
Figure 1. 3: The trend of scientific citations per patent in France (1990-2015) .....	45
Figure 1. 4: The average of regional scientific expertise of regions (1994-2013).....	50
Figure 1. 5 (a,b,c): The average of regional scientific expertise of regions (2000-2007).....	52
Figure 1. 6 (a, b, c): The scientific expertise of regions in 2000 .....	54
Figure 1. 7: The average of regional technological expertise of regions (1994-2013).....	57
Figure 1. 8 (a, b, c): The average of regional technological expertise of regions (2000-2007)....	59
Figure 1. 9 (a, b, c): The scientific expertise of regions in 2000 .....	62
Figure 1. 10 (a, b, c): The interdependence between different types of national scientific and technological expertise.....	66
Figure 1. 11: The relationship between interdependence and technological expertise index of regions.....	68

## List of Tables

Table 2. 1: Descriptive data .....	92
Table 2. 2: Correlation matrix.....	93
Table 2. 3: Regression analysis of the characteristics of regional scientific expertise on the time lag.....	96
Table 2. 4: Robustness checks for the sample between 1994-2004.....	97
Table 2. 5: Regression analysis of the characteristics of regional scientific expertise on the forward patent citation counts.....	98
Table 2. 6: Regression analysis of the characteristics of regional scientific expertise on the forward patent citation counts. Robustness checks for the sample between 1994-2004 .....	99
Table 3. 1: Descriptive data .....	133
Table 3. 2: Correlation matrix.....	134
Table 3. 3: Negative binomial regression with region fixed-effects. Determinants of innovation's performance .....	137
Table 3. 4: The robustness of the results. Testing alternative models .....	138
Table 3. 5: Determinants of explorative inventive performance .....	139

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## Introduction

My dissertation investigates on how local inventors/firms innovate under a regional-specific context. The question is initially inspired by the literature on agglomeration economies, which emphasize the localized knowledge diffusion (Feldman 1994). Following this idea on regional growth, an evolutionary economic geography approach asks whether the knowledge diffusion takes place between any industrial sectors (Frenken, Oort, and Verburg 2007). The underlying concept of “related variety” is that local sectors benefit from complementary knowledge. Their results show that related industrial sectors have an impact on regional branching (Boschma and Frenken 2010; Neffke, Henning, and Boschma 2011). This stream of research suggests the related variety as a mechanism for knowledge diffusion (Boschma 2017; Content, Frenken, and Jordaan 2019). Another literature of knowledge bases also questions how knowledge diffusion happens over the process of knowledge creation. The underlying idea of this question is the nature of specific knowledge input for the innovation (Moodysson 2008; Moodysson, Coenen, and Asheim 2008). As growing complexity and diversity of contemporary knowledge for innovation, inventors are generally embedded into knowledge networks and, accordingly, acquire new knowledge to complement their knowledge bases (Asheim, Boschma, and Cooke 2011; Chesbrough 2003). This stream of research has quantified the differentiated knowledge bases and empirically tested their impacts on regional innovation performance (Asheim et al. 2011; Asheim and Hansen 2009; Blažek and Kadlec 2019; Grillitsch, Martin, and Srholec 2017; Květoň and Kadlec 2018; Martin 2012).

With the aims to understanding how regions diversify into new growth paths, Asheim et al. (2011) integrate the notion of relatedness with differentiated knowledge bases to construct

regional advantage. The underlying idea is to facilitate knowledge diffusion across local actors concerning the nature of knowledge and their relatedness. In a similar vein, Grillisch et al., (2018) revisit the regional structure change by distinguishing different forms of path development of regions. In this study, the authors highlight the scientific discoveries as a source for the emergence and growth of entirely new industries. This regional strategy of path creation is as an outcome of search processes. My dissertation is geared to this line of research. More specifically, the thesis tends to uncover the dynamics of regional knowledge expertise and examine the sources of effect on the innovative performance of local inventors. It contributes to the geography of innovation by the three essays that are detailed below.

Within regional innovation systems, there are mainly two interconnected subsystems (Autio 1998; Cooke 2002). On the one hand, there is the knowledge-generation subsystem that primarily comprises of universities, public research organizations. On the other hand, the knowledge exploitation subsystem mainly consists of industrial firms. Such knowledge subsystems have embedded the learning processes of local actors, that facilitate their innovative capacities (Asheim and Gertler 2006; Moodysson et al. 2008). Moreover, Todtling and Trippl (2005) argue that the RIS draws attention to the local firms and organizations of an innovation system, to the interdependencies within the region and with other regions, and to the higher spatial levels (national, international). In this system, key actors from both private and public sectors simultaneously explore and exploit new knowledge (Isaksen and Karlsen 2011). Indeed, Blazek and Kadlec (2019) distinguish different types of R&D system in terms of private, higher education and governmental institution and study. They show that the regional knowledge bases and R&D structure are systematic and mutually interwoven.

Moreover, when Asheim and Coenen (2005) conceptualize the different types of regional knowledge bases, they argue that:

*“The innovation process of firms and industries is particularly dependent on their specific knowledge base”.* (page 1176).

And they define:

*“An analytical knowledge base refers to industrial settings, where scientific knowledge is highly important, and where knowledge creation is often based on cognitive and rational processes, or on formal models”* (page 1176).

These concepts emphasize that firms not only use their knowledge competencies but also rely on the scientific results of universities and other research institutions for their innovation generation. These studies conceptually highlight the important characteristic of interactive learning for local inventors in accessing new fast-growing knowledge across organizational domains, economic sectors and scientific disciplines (Asheim et al. 2011; Manniche 2012; Strambach and Klement 2012). However, the knowledge base taxonomies, which rely on the occupation classification, could not empirically capture the characteristic of knowledge dynamics and the variation of knowledge bases (Manniche, Moodysson, and Testa 2017). As a result, such a research line could not unpack learning processes (Bathelt 2006; Manniche et al. 2017).

On the other hand, the technological relatedness is considered as a mechanism for knowledge diffusion between related sectors, thus, is a potential source for emerging new technology in the region (Boschma et al. 2014, 2015; Frenken, Oort, and Verburg 2007). However, the relatedness largely ignores the role of unrelated knowledge in the processes of innovation

creation (Grillitsch, Asheim, and Trippel 2018). Furthermore, most studies under this line of research focus on the relatedness of industrial sectors within the region rather than related and unrelated sources on a non-local scale (Trippel, Grillitsch, and Isaksen 2018). As a result, Grillitsch et al. (2018) ground their conceptual framework by combining unrelated knowledge with existing competencies in the region. However, it seems that the notion of unrelatedness is regarded as the relative relationships between technological knowledge elements rather than those between scientific and technological knowledge. Indeed, the study defines the difference between regional path diversification and creation. As such, regional path diversification is as an outcome of combination between the existing knowledge base with new, unrelated knowledge elements. Furthermore, regional path creation is as a result of applying scientific discoveries into the existing technology.

The dissertation argues that the relative relationships between science and technology. The degree of their linkages implies the frequent co-occurrences between them. We claim that the less observed co-occurrence indicates the unrelatedness or independent relationship. In contrast, the high frequent co-occurrence suggests the relatedness between them. As a result, under the view of inventors who are searching for new knowledge for their innovative activities, this dissertation emphasizes the interdependences between science and the local industry. Indeed, the scientific material is a mechanism to explain the diffusion of knowledge between the local innovation and future technologies (Ahuja and Katila 2004; Fleming and Sorenson 2004; Gittelman 2016; Lim 2004; Narin et al. 1997; Nelson 1959). More than the benefits of relatedness, this dissertation argues that the dynamic relationship between each pair of science and technology could provide more fruitful sources of knowledge.

The interdependence between different types of knowledge is an essential factor for the innovation performance of firms because it indicates the interaction between science and technology (Heinisch et al. 2016; Martin and Sunley 2006; Meyer 2000; Narin, Hamilton, and Olivastro 1997; Van Looy et al. 2006; van Vianen, Moed, and van Raan 1990). These relationships imply diffusion of knowledge across actors not only in geographical proximity but also in the spatial distance (Belenzon and Schankerman 2013; Michaël Bikard 2018; Michaël and Matt 2019). As a result, at the aggregated level, particularly in the country level, the dynamic relationships between science and technology can provide many potential search directions. Local actors can have different trajectories to identify themselves on the knowledge chain and to predict the fruitful direction for combining different knowledge elements. It helps to map innovation networks (Ribeiro et al. 2018) and to shape the innovation system (Patelli et al. 2017). If the region does not specialize in a specific scientific knowledge field, but has an advantage in a specific technology, which is potentially synergized to scientific field in other regions, the local inventors could be able to realize and capture that distantly scientific knowledge.

### *Chapter 1: R&D and knowledge expertise of French regions*

In this chapter, I initially take the first step to unpack the regional context underlying the process of knowledge generation. Then I describe the dynamic evolution of the regional knowledge elements and the connectedness between them and the R&D expenditure. Particularly, this chapter is geared to towards answering whether there is any specific trend or tendency in the relationships between regional R&D expenditure and numbers of expertise field and level of expertise. In addition, the subquestion is whether there is the connectedness between the level of

interdependence between science and local technology and the level of expertise of the focal technology in the region.

The chapter uses French published patents and scientific publications (1990-2015) to construct different types of regional knowledge expertise. The unit of analysis is at the department (NUTS3) level. We build a comprehensive scheme of analysis of regional knowledge expertise, which mainly focuses on technological and scientific knowledge. These types of knowledge expertise are fine-grained layers of the RISs that be distinguished into different scientific fields and technological domains. In this study, scientific knowledge expertise is measured by scientific publications of scientists and researchers affiliating in the region, which presents the knowledge generation subsystems. The technological knowledge expertise is proxied by technological patents claimed by local inventors living in the region, which reflects the knowledge exploitation subsystem.

Moreover, the citation of a patent to a scientific publication indicates the interaction between two subsystems. Our data of publication-patent citations help us to track up these relationships at the higher spatial levels (national, international). Because the interdependences are observed according to the citation patterns of all French inventors, we could imply these to understand the relatedness between science and local technology.

We then observe the types of knowledge expertise, particularly scientific and technological expertise, in the RISs. Second, we investigate the connectedness of R&D expenditure and the regional knowledge expertise in the RISs. Third, the study also examines the relationship between potential complementary of the RISs and technological knowledge expertise.

The results show that different types of regional knowledge expertise may provide many insights about local scientific and technological trajectories. In particular, regional expertise is quite heterogeneous. It also reveals how regions develop and gain competitive advantage. Not surprisingly, the findings demonstrate that R&D expenditure has a positive relationship with the numbers of the scientific and technological expertise of the region. However, the level of regional expertise is not related to R&D expenditure. Last, the level of technological expertise will increase if it highly relates to a scientific field that is complementary to the focal technology.

The chapter contributes to the current literature in several aspects. First, the findings are consistent with the characteristics of regional knowledge bases, which are cumulative and path-dependent (Asheim and Coenen 2005; Asheim and Gertler 2006; Martin 2012). Second, the results also align with the concept of relatedness, which is a potential source for emerging new technology in the region. More than the benefits of relatedness, this chapter shows that the dynamic relationship between each pair of science and technology could provide more fruitful sources of knowledge. Thirdly, we also add to the management literature of innovation generation that inventors can identify, select and combine different elements of scientific knowledge (Ahuja and Katila 2004; Fleming and Sorenson 2004; Gittelman 2016; Lim 2004; Narin et al. 1997; Nelson 1959). The map of their interdependences could guide them to search for new knowledge.

*Chapter 2: The time value of local scientific expertise* (Co-authored with Ludovic Dibiaggio<sup>1</sup> and Maryann Feldman<sup>2</sup>)

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The second essay explicitly examines the role of local scientific expertise for the processes of innovation. In this chapter, we extend the notion of localized knowledge diffusion between science and technology. More specifically, while scholars have extensively investigated different mechanisms for the localized knowledge diffusion between technologies, there is no study to answer “what is the mechanism for the diffusion of knowledge between a scientific publication and technological innovation”. This chapter aims to answer the above question.

We adopt the current literature about the relationship between science and technology. We try to understand under which condition inventors may refer to scientific publication. Then we predict the outcome of the search process. We argue that science should be correspondent to the focal technologies to bring benefits to local inventors. In addition, the underlying mechanism of scientific expertise is also applicable to the diffusions of knowledge across innovations. The basic idea is that patents reference the scientific literature, which reflects broad dissemination of public knowledge, receive more citations. The effect indicates the norm of the diffusion of knowledge (Sorenson and Fleming 2004; Sorenson and Singh 2007).

We analyze the dyads between patent and scientific (peer-reviewed) publication. We measure the time lag between the published year of cited publications and citing patent to captures the diffusion of knowledge from scientific publication to the invention. The second model tests the impact of the underlying mechanism on the rate of diffusion of knowledge across technological innovations. French patents are associated with technological classes (WIPO)'s classification to distinguish the different technological groups in our samples. The French scientific papers are classified into scientific fields based on the classification of WoS Journal Subject Categories

developed by Thomson Reuters. This dataset is used to construct the scientific expertise in the region.

Our result shows that the local scientific expertise, which is relevant to the focal technological innovation, decreases the time lag between publication-patent citation as well as increase the future citations received by the focal patent. The results are consistent with the idea that scientific expertise accelerates the diffusion of information between science and technology as well as between technologies. Rather than rely on the published materials claimed in the focal innovation, we examine the antecedent of scientific references reported in the technological innovation. This helps us to explain the mechanisms behind the difference in the time lag between publication-patent links. Therefore, the paper will help scholars to better understand the different mechanisms for the diffusion of knowledge and/or interplay between science, innovation and technological progress.

We believe that this question is an important one, not only because science is generally assumed to be a source for innovation, but also because it helps to understand the process of referencing or of identifying the useful scientific publications. If we can understand the underlying mechanism for this process, we may be able to deliver appropriate strategies and policies at different levels: inventor-, firm-, industry-, regional-, and national levels.

In practical relevant, answering these questions help different stakeholders to have better strategies and policies relating to the linkage between science, innovation and technological progress. From an R&D policy' perspective, understanding the underlying mechanism to reference scientific publications of inventors may help policymakers to guide and accelerate the scientific investment. For industry, the diffusion of knowledge of science may help industrial sectors to

rejuvenate its innovation advantage by acquiring potentially scientific knowledge faster. Consequently, patents, which cite scientific publications, have better impacts on future technology. Firms and inventors may have oriented-direction of search and of combining the newly acquired knowledge.

*Chapter 3: Regional alignment and innovative performance of regions (Co-authored with Ludovic Dibiaggio and Benjamin Montmartin<sup>3</sup>)*

The third chapter broadens the second chapter by integrating regional scientific and technological knowledge expertise. We further argue that the interdependences between them generate the knowledge platform, which enhances the processes of the invention. More specifically, this chapter examines how and what extent regions may provide knowledge platforms contributing to developing local inventors' innovative and explorative capabilities. To answer the question, we theoretically conceptualize and empirically test the mechanisms that may affect the regional innovative performance of regions.

Particularly, we elaborate on the concept of regional alignment (RA) as a potential explanation for the effectiveness of knowledge platforms. Regional alignment characterizes potential synergies between complementary and heterogeneous knowledge bases, competencies and skills across local agents. Moreover, regional alignment reflects expertise in sciences, technologies and businesses that have synergistic effects when combined. Regional alignment enacts knowledge platforms because it reveals knowledge and social networks among academic, business and institutional actors facilitating access to external knowledge and increase absorptive

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<sup>3</sup> SKEMA business school, Université Côte d'Azur

capacities. Therefore, regional knowledge expertise may mitigate the risk and uncertainty of knowledge creation.

We find a positive relationship between regional alignment and innovative performance. More interestingly, regional alignment has a positive effect on explorative activities of local inventors or firms. In addition, regional alignment has a negative coefficient with the rate of exploration and a positive coefficient with forward citation-weight of explorative patents. The results show that regional alignment provides local actors with higher explorative capabilities to search and evaluate the distant knowledge. Therefore, it helps to reduce variance and increase the usefulness of their explorative innovations. Thus it confirms the idea of regional alignment as a knowledge platform that plays a vital role in inventive regional capacities.

This chapter contributes to the literature of economic geography by examining the mechanism underlying the process of knowledge generation in the regional specific context. More specifically, the panel data on regions in terms of patenting activity that individual inventors play the majority role of knowledge creation.

This study also speaks to the literature of innovation management. While the current studies emphasize the localized knowledge sources that inventors can search for (Gittelman and Kogut 2003; Jaffe and Trajtenberg 1996; Zucker et al. 2007; Zucker, Darby, and Armstrong 2002), scholars still do not know which scientific knowledge inventors build on and how the role of the geographically distant knowledge is to local inventors. We suggest that the regional knowledge expertise and its potential synergy to other counterparts of scientific knowledge facilitate local inventor the direction of their search. Therefore, they might have an appropriate strategy to acquire and to combine the new knowledge.

## **Chapter 1**

### **R&D and Knowledge Expertise of French Regions**

## **R&D and Knowledge Expertise of French Regions**

### **Abstract**

Within the literature of regional innovation systems, a growing stream of research emphasizes the role of differentiated knowledge bases. The employees' occupations mainly measure the existing work on knowledge bases. Even though the conceptual theory highlights the importance of interactions across types of knowledge bases underlying innovation activities, they are separately measured and treated in most empirical studies. While few studies use the interaction term between knowledge bases, it does not reflect their actual relationships. In this study, an attempt is made to analyze and observe the regional knowledge for long periods of time. The study suggests measuring different types of expertise in science and technology of the region, as the fine-grained layers of regional knowledge bases, by using patent and publication datasets in France. Finally, we imply the new measurements to understand the relationships between regional R&D expenditure and their knowledge expertise. The results show that R&D expenditure has a positive relationship with the numbers of the scientific and technological expertise of the region; however, not to the level of expertise. The results also show that the level of technological expertise will increase if it is complementary to a specific science.

**Key words:** *regions, science, technology, interdependence, R&D*

## **Introduction**

Over the last decades, scholars in the geography of innovation have paid their attention to understanding the relationship between geography and knowledge creation (Asheim et al. 2011; Cooke 2002; Feldman and Florida 1994; Marshall 1920). One of the most recent research streams is the theory of regional innovation systems (RIS) (Asheim et al. 2011; Asheim and Gertler 2006; Cooke, Gomez Uranga, and Etxebarria 1997; Moodysson et al. 2008). This literature emphasizes the role of spatial proximity, which facilitates interactive learning processes between local actors in various industries, governments and academies (Boschma 2005).

Within this literature, the RIS consists of two interconnected subsystems (Autio 1998; Cooke 2002). On the one hand, there is the knowledge-generation subsystem that primarily comprises of universities, public research organizations. On the other hand, the knowledge exploitation subsystem mainly consists of industrial firms. Such knowledge subsystems have embedded the learning processes of local actors, that facilitate their innovative capacities (Asheim and Gertler 2006; Moodysson et al. 2008).

Asheim and Gertler (2005) have recently distinguished different types of regional knowledge bases in the RISs. In particular, an analytical knowledge base refers to activities relating to scientific knowledge that relies on codified and formal models (Asheim and Coenen 2005). Examples are science in bioinformatics, genetics and nanotechnology. Knowledge inputs and outputs in this type of knowledge base are often acquired through university and industry linkages. Additionally, codified knowledge is more frequent than other types of knowledge base because knowledge inputs and analytical skills for abstraction, theory-building and testing are

mainly based on existing studies and scientific principles. Therefore, knowledge outputs are generally radical knowledge.

Meanwhile, a synthetic knowledge base refers to activities relating to tacit knowledge which takes place through solving the problem or recombining of existing knowledge (Asheim and Gertler 2006). Examples are chemical engineering, computer technology, and audio-visual technology. Knowledge inputs and outputs in this type of knowledge bases may be acquired through university-industry links, but are more in the field of applied research than in the basic research. Besides, tacit knowledge is more frequent than other types of knowledge base because knowledge inputs and technological skills for testing, applying and experimenting are primarily based on practical work and learning by doing (Asheim et al., 2011). Hence, knowledge outputs are often incremental knowledge.

Following the above idea, an large stream of research has quantified the differentiated knowledge bases and empirically tested their impacts on regional innovation performance (Asheim et al. 2011; Asheim and Hansen 2009; Blažek and Kadlec 2019; Grillitsch et al. 2017; Květoň and Kadlec 2018; Martin 2012). However, these studies face several limitations.

First, by using data on employees' occupations to measure firm or regional knowledge bases, the method overlooks the possible discrepancy between main activities registered in the occupation classification and the actual activities carried out in the firm (Manniche et al. 2017). For example, company A may employ many scientists to deal with production and development and only a few engineers to support the production lines. Scientists who are employed by the company to do the tasks of production and development do not involve scientific research. Even though the activity of the company is heavily carried out on a synthetic (engineering-based)

knowledge base, its composition of the occupation reflects on the analytical (science-based) knowledge base.

Second, the main characteristic of the interactive learning process is that inventors access new fast-growing knowledge across organizational domains, economic sectors and scientific disciplines (Asheim et al. 2011; Manniche 2012; Strambach and Klement 2012). However, the knowledge base taxonomies, which rely on the occupation classification, could not capture the characteristic of knowledge dynamics and the variation of knowledge bases (Manniche et al. 2017). On the one hand, there are different types of knowledge (i.e. codified v.s tacit knowledge), which reflects its transferability and nature (Gavetti and Levinthal 2000; Gittelman 2016; Narin et al. 1997; Nelson 1959). On the other hand, the evolution of RISs and relationship across them also transform over time, which significantly affect innovation performance (Blažek and Kadlec 2019; Kvētoň and Kadlec 2018). These studies tend to overlook the dynamics of regional knowledge bases, and also their relative relationships (across science and technology). Indeed, scientific research is a complex and multifaceted activity, which is time-dependent and context-dependent (Tijssen 2010). Thus, knowledge generation should adhere well to this evolution.

Moreover, Todtling and Trippl (2005) argue that the RIS draws attention to the local firms and organizations of an innovation system, to the interdependencies within the region and with other regions, and to the higher spatial levels (national, international). In this system, key actors from both private and public sectors simultaneously explore and exploit new knowledge (Isaksen and Karlsen 2011). Therefore, Blazek and Kadlec (2019) distinguish different types of R&D system in terms of private, higher education and governmental institution and study. They further study the mutual relationships among knowledge bases, R&D structure (R&D expenditure and

employees) and innovation performance of European NUTS2 regions. The results show that the regional knowledge bases and R&D structure are systematic and mutually interwoven. However, these studies could not capture the evolution, structure and the dynamic relationships of actors, institutions in the RISs (Blažek and Kadlec 2019; Uyarra and Flanagan 2010).

This study aims to contribute to this stream of research. We build a comprehensive scheme of analysis of regional knowledge expertise, which mainly focuses on technological and scientific knowledge. One can assume that these types of knowledge expertise are fine-grained layers of the RISs that be distinguished into different scientific fields and technological domains. In this study, scientific knowledge expertise is measured by scientific publications of scientists and researchers affiliating in the region, which presents the knowledge generation subsystems. The technological knowledge expertise is proxied by technological patents claimed by local inventors living in the region, which reflects the knowledge exploitation subsystem.

Moreover, the citation of a patent to a scientific publication indicates the interaction between two subsystems<sup>4</sup>. Our data of publication-patent citations help us to track up these relationships at the higher spatial levels (national, international). Because the interdependences are observed according to the citation patterns of all French inventors, we could imply these to understand the internal relationships of RISs.

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<sup>4</sup> The relationship between science (publications) and technology (patents) is extensively discussed in recent works (Callaert, Pellens, and Van Looy 2014; Narin, Hamilton, and Olivastro 1997; Patelli et al. 2017). Some scholars argue that science as a source of knowledge for innovation processes (Ahuja and Katila 2004; Bikard and Marx 2018; Fleming and Sorenson 2004). However, other studies show that science (publications) cited by a patent is only as background information, which indicates whether a scientist has published something relevant (Meyer 2000; van Vianen et al. 1990). In this chapter, we only observe the patterned relationship between science and technology without arguing about the effect of this relationship on innovation creation. As a consequence, the terms of "interdependence" and "relationship" are interchangeably used.

Therefore, the objective of the study is to observe the types of knowledge expertise, particularly scientific and technological expertise<sup>5</sup>, in the RISs. Second, we investigate the connectedness of R&D expenditure<sup>6</sup> and the regional knowledge expertise in the RISs. Third, the study also examines the relationship between potential complementary of the RISs and technological knowledge expertise. Thus, the key research question emerges, whether there is any specific trend or tendency in the relationships between regional R&D expenditure and numbers of expertise field and level of expertise. In addition, the subquestion is whether there is the connectedness between the level of interdependence between a specific pair of technology and science at the national level and level of expertise of focal technology in the region.

The chapter uses French published patents and scientific publications (1990-2015) to construct different types of regional knowledge expertise. The unit of analysis is at the department (NUTS3) level. The results show that different types of regional knowledge expertise may provide many insights about local scientific and technological trajectories. In particular, regional expertise is quite heterogeneous. It also reveals how regions develop and gain competitive advantage. Not surprisingly, the findings demonstrate that R&D expenditure has a positive relationship with the numbers of scientific and technological expertise of the region. However, the level of regional

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<sup>5</sup> There are three types of knowledge base: analytical, synthetic and symbolic (Asheim and Gertler 2006). However, this chapter only refers to two types of the regional knowledge base. First, we pay more attention to the process of interactive learning underlying knowledge generation, where the concept of synthetic (engineering-based) and analytical (science-based) knowledge are more relevant to our research questions. Second, because our datasets are only available on scientific publications and patents, we could construct our measurements that reflect these types of knowledge.

<sup>6</sup> Regional R&D structure, which comprises of both R&D employees and expenditure, is investigated across regions (Blažek and Kadlec 2019). However, the share of R&D employees in different types of knowledge bases (analytical, synthetic, symbolic) is not connected to the R&D expenditure in the region. In our study, we want to test this relationship at the fine-grained level of knowledge expertise rather than the aggregated level of regional knowledge bases.

expertise is not related to R&D expenditure. Last, the level of technological expertise will increase if it highly relates to a scientific field that is complementary to the focal technology.

The chapter is structured as follows. First, we review the theoretical literature of regional knowledge. Second, we introduce measurements of regional expertise and interdependence between different types of knowledge expertise. The results are explained to provide insights into regional knowledge expertise. Finally, the conclusion part discusses further research on the topic.

### **The theoretical concept of regional knowledge expertise**

#### *The different types of regional knowledge expertise*

As the growing complexity and diversity of contemporary knowledge needed to create innovation, inventors are commonly embedded in knowledge networks (Chesbrough, 2003). Thus, distinguishing different types of knowledge bases could help to understand the nature of knowledge inputs on which invention activities are taken (Moodysson, 2008). It also means that external knowledge may be a critical asset for innovation. As inventors are a part of distributed knowledge networks and of value chains of knowledge processes, new knowledge is more increasingly nested into a various level of systems (e.g. regional, national and international levels) (Asheim et al., 2011). The firm's knowledge is not only internally used but also potentially distributed and diffused to external actors. Particularly, when knowledge diffusion takes place among local agents, this eventually enhances regional knowledge bases in which there are mixes of complementary scientific and technological knowledge, competencies, qualifications and skills (Audretsch and Feldman 2004; Feldman and Florida 1994). Different types of knowledge are variously sensitive to geographical and social distance. While engineering-based knowledge has

the property of stickiness that makes it more sensitive to spatial and social distance (Asheim and Gertler 2006; Herstad, Aslesen, and Ebersberger 2014; Moodysson et al. 2008), science-based knowledge is less sensitive to geographical distance (Herstad et al. 2014; Martin and Moodysson 2013; Plum and Hassink 2011).

Engineering-based knowledge in the region comprises of a variety of technologically industry sectors. Then, synthetic knowledge base must be able to explain industry-specific differences because the degree of localised knowledge diffusion is various across technological areas (Belenzon and Schankerman 2013; Faggio, Silva, and Strange 2017; Martin and Moodysson 2013; Plum and Hassink 2011). Indeed, Belenzon and Schankerman (2013) show that in some industrial sectors where information is less codified, thus harder to transmit (i.e. biotechnology, pharmaceuticals, and chemicals), diffusion of knowledge is more sensitive to spatial distance than those in electronics, information technology, and telecommunications. Besides, Faggio and colleague (2017) find that the variation in characteristics of industries also exposes differently to types of agglomeration. More specifically, high-technology industries show stronger evidence of localised knowledge diffusion rather than low-technology sectors. In short, the regional engineering-based knowledge should be divided into sub-categories, which may provide an in-depth understanding of the knowledge creation process of local actors.

In a similar argument in engineering-based knowledge, it is vital to classify science-based knowledge to a variety of scientific fields (domains). However, the likelihood that inventors citing scientific publications depend on the quality and usefulness of scientific results for their new knowledge generation (Michaël Bikard 2018; Michaël and Matt 2019). Audretsch and Feldman (1996) show that scientific results are not necessarily useful for every industrial sector. Indeed,

scientific research (publications) is only useful to electrical and pharmaceutical sectors rather than mechanical and chemical sectors (Leten, Landoni, and Van Looy 2014). Besides, Lim (2004) shows that the pharmaceutical industry mainly depends upon both basic and applied scientific research, while the semiconductor industry is closely tied to applied research. The usefulness of scientific publications is heterogeneous not only between technological industries but also within an industry. In particular, in the biopharmaceutical sector, the purpose of basic research is attempting to build fundamental knowledge of biological processes and to reveal the underlying mechanisms and processes of disease. The purpose of applied research aims to generate practical knowledge related to human diseases such as clinical trials, therapeutic interventions, dosage testing and information about drugs (Gittelman 2016; Lim 2004). Thus, it is reasonably argued that classifying science-based knowledge into different fields (domains) could help to understand the specific value of each scientific field.

### *The dynamic relationships between science and technology*

If the region possesses different types of scientific knowledge, the geographic proximity may generate interactive learning among universities, research organisation and firms. The regional knowledge is not only a critical source of innovation (Asheim et al. 2011; Asheim and Coenen 2005; Grillitsch et al. 2017) but also help local inventors to recognise the potential knowledge (Michaël Bikard 2018; Michaël and Matt 2019). However, the institutional characteristics of science also make the diffusion of scientific knowledge (publications) not being geographically bounded. First, rather than inventors, who focus on the particular technological innovation, scientists generally refer to tackle more fundamental problems that can potentially be applied in a broader range (Henderson, Jaffe, and Trajtenberg 1998). Second, the characteristic of

“winner-take-all” rewards surrounding first discovery engenders scientists to publish their findings (Merton 1957). Thirdly, the norm of openness of science also offers an effective means to disseminate it to the scientific community because scientists can establish and claim their findings (Merton 1957). Taken together, these scientific institutions promote the diffusion of knowledge not only locally but also widely.

The question arises to what extent the local inventors and firms could benefit from the knowledge bases available in the region. In order to capture and identify potential knowledge, local actors must position different types of local knowledge files. Local inventors further acquire new knowledge or try different knowledge combinations. Then, the following question is "what if the set of science- and technology-based knowledge in the region has the interdependent relationship with other scientific and technological knowledge existing in other regions". In this case, the studies show that firms will engage in the inter-regional knowledge exchange (Fitjar and Huber 2015; Grillitsch and Nilsson 2015). The interdependence between different types of knowledge is an essential factor for the innovation performance of firms because it indicates the interaction between science and technology (Heinisch et al. 2016; Meyer 2000; Narin et al. 1997; Van Looy et al. 2006; van Vianen et al. 1990). These relationships imply diffusion of knowledge across actors not only in geographical proximity but also in the spatial distance (Belenzon and Schankerman 2013; Michaël Bikard 2018; Michaël and Matt 2019).

As a result, at the aggregated level, particularly in the country level, the dynamic relationships between science and technology can provide many potential search directions. Local actors can have different trajectories to identify themselves on the knowledge chain and to predict the fruitful direction for combining different knowledge elements. Indeed, the pattern of science-

technology citation reflects whether a country's technologies keep in space with sciences (van Vianen et al. 1990). It helps to map innovation networks (Ribeiro et al. 2018) and to shape the innovation system (Patelli et al. 2017). If the region does not specialize in a specific scientific knowledge field, but has an advantage in a specific technology, which is potentially synergized to scientific field in other regions, the local inventors could be able to realize and capture that distantly scientific knowledge.

## **Methodology for measuring knowledge expertise**

### *Units of analysis and indicators*

Before collecting data and constructing variable, it is essential to decide on units of analysis and indicators that are suitable for this study. As argued in section 2, we take the concept of regional knowledge bases to dig into the fine-grained level of knowledge, which is named sub-categories.

Regarding science-based (analytical) knowledge, we refer the regional scientific expertise (RSE). In each region, there are different types of scientific expertise that have different values to specific technological industries. The early work of classifying biomedical scientific journals, ranging from most basic to applied, was based on expert assessments responding to its research level (Narin, Pinski, and Gee 1976). The classification system was further expanded by adding other scientific fields (i.e. physical sciences (Boyack et al. 2014; Boyack and Klavans 2011; Carpenter M. et al. 1988). Later, the word-based approach was applied to classify scientific publications (Cambrosio et al. 2006; Lewison and Paraje 2004). Recently, Tijssen (2010) used the

knowledge utilization approach to classify journals into six categories: academic, industry-relevant, industry practice, clinical relevant, clinical practice and industry-clinical relevant.

Even there are different approaches to design journal-level taxonomies; there is no single classification system widely adopted by the international bibliometric community and governments (Archambault, Beauchesne, and Caruso 2011; J. S and D. 1995). In addition, there are several pitfalls in the existing classifications such as journal disciplines change at a faster rate than those in the classification systems, delimiting a scientific field at the journal level is not as accurate as those at the article level, etc<sup>7</sup>. Science-Metrix classification, which is partially funded the European Commission, is modelled on those of existing classifications (i.e. Thomson Reuters' Science Citation Index-ISI, CHI journal classification, The Australian Research Council Evaluation of Research Excellence-ERA). The new classification has several advantages: 1) it is available in eighteen languages, 2) it is an open-source that anyone can contribute to modify, and 3) it comprises of the vast majority of scientific journals existing in both Scopus and Web of Science (WoS). This chapter assigns different types of scientific expertise base on this classification system.

Regarding engineering-based (synthetic) knowledge, we refer to different types of regional technological expertise (RTE). Most classifications use the information about the firm's principal activities, the sectors of product outputs, and the sources of knowledge input for production (Pavitt 1984; Peneder 2010). However, firms differently use knowledge input and produce various products; international comparisons are difficult. Besides, production is based on technologies, and different products use different technologies. Patents are oriented to protect the specific

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<sup>7</sup> Further details, please refer to Archambault, et al., 2011 and Gomez et al., 1996

technologies used in a patent (Schmoch 2008). There are several technology classifications, such as the International Patent Classification (IPC), the US Patent Classification (USPC) and the Japan Patent Office (JPO). Besides, there is the Cooperative Patent Classification (CPC)- an extension of IPC. It has been created in 2013 and is maintained by EPO and the US patent office. Many patent offices increasingly use this classification. However, all classification systems are inconsistent in philosophy and approach, which reflect in the classification system design (Harris, Arens, and Srinivasan 2010). In particular, the USPC classification consists of over 163,000 entries, which represents each patent function as a single class and subclass. In contrast, IPC assigns a patent to one or more of the 71,000 IPC codes that relate to the technical field(s) the patent covers. The depth of the USPC gives more precise information on the real purpose of the invention. However, it also is more challenging to search.

Meanwhile, a search across the broader technical categorization in the IPC system may give a wider variety of patents, which return to more precision. The Fraunhofer ISI, the Observatoire des Sciences et des Technologies (OST) and the French patent office (INPI) cooperate in developing a more systematic and comparable technology classification that bases on the codes of IPC. The first version was released in 1992 and comprised of twenty-eight technology classes (Grupp and Schmoch 1992). The updated version of the ISI-OST-INPI classification was released in 2005, which consisted of thirty classes. The third version was released in 2008. The present chapter applies the latest version of the ISI-OST-INPI classification (2008) to classify different types of technological knowledge expertise.

### *Data collection*

We collect three different datasets to measure regional scientific, technological knowledge expertise and the interdependence pairs of each technology and science field. In addition, the analysis is for France and the region is defined at the NUT3 or department level.

The 743,693 French patents granted by the European Patent Office from 1990 to 2015 is retrieved from the PATSTAT database (version fall 2015). Each patent provides information about the application year, the priority year, the publication year, the inventors of the patent, and citations to patents previously granted or to non-patent prior-art references (NPRs).

Most of the previous studies use the published (granted) year of patents as a time for their observed periods (McMillan, Narin, and Deeds 2000; Narin et al. 1997; van Vianen et al. 1990). This chapter applies the priority year of patents to construct the period of observations because that year is as the specific time when the patent activities are carried out. Generally, the difference in years between the priority year and the published year of a patent is about 1-3 years for French patents (figure 1).

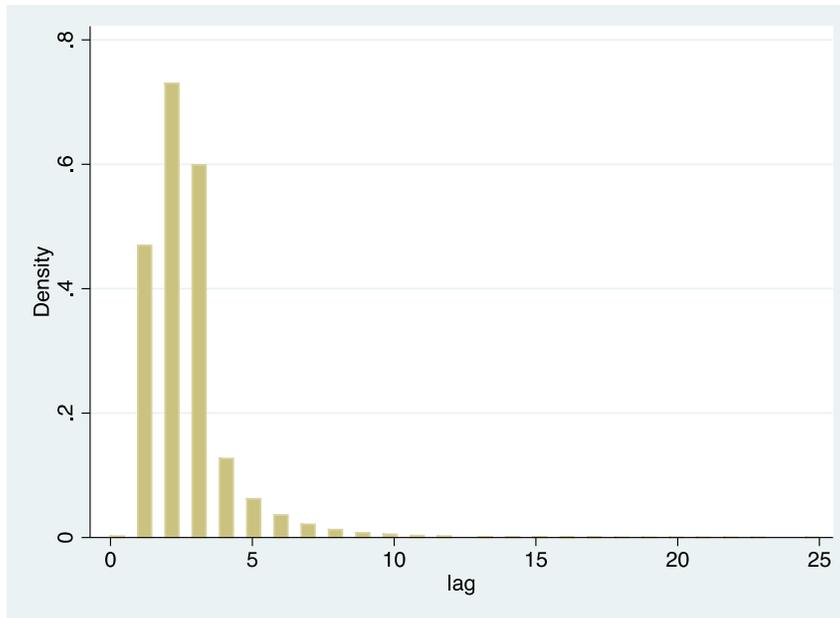


Figure 1. 1: The distribution of the difference in years between the priority year and the published year of a patent

***Data for regional technological knowledge expertise***

Among 743,693 patents, there are only 114,244 patents that have information about the address of inventors (such as zip code, city name). Inventor’s location is a reliable proxy to indicate the place where innovation was developed (Ter Wal, 2013; Leten et al., 2014). If there are many inventors of a patent claiming in the same region, we record only one observation for that region. At the aggregated level, the sum of total patents in a region also reflects its technologies. Therefore, we discard the locations of patent's applicants (or assignee) because these are often the headquarters’ addresses rather inventors’ location. Technological characteristics of patents are based on the International Patent Classification (IPC), which assigns each patent to one or several pre-define technological classes. We use the last version of the IPC, consisting of 35 technological classes (Schmoch 2008). This technology classification allows us to measure regional knowledge in each technology domain yearly.

### *Data for regional scientific knowledge expertise*

To measure regional scientific expertise in each specific domain we collected all scientific articles published by French authors<sup>8</sup> and assigned them to a pre-defined scientific domain. More precisely, we extracted 1,481,784 scientific articles published by a French author between 1990 to 2015 from Thomson Reuters' Web of Science (WoS). Then, relying on the academic journal where it has been published, each paper was then assigned to one of the 22 scientific domain as provided by the Science-Metrix journal classification (Archambault et al. 2011)<sup>9</sup>. Science-Metrix classification assigns each individual journals to single, and mutually exclusive categories. Although publications and authors' activity increasingly rely on interdisciplinary work and may be assigned to several scientific fields or subfields (Glänzel and Schubert 2003), the allocation to several fields or subfields may create ambiguous information and prevent consistent comparison exercises (Gómez et al. 1996a). Then, using the postcode of the address of the author's affiliation, each paper was allocated to a French region. Similar to the geographic allocation of patents, co-authored papers may have been allocated to several regions if co-authors work in different regions.

As figure 2, there is a decreasing trend of patent data in the latest years. There are several reasons. First, the dataset was released in Autumn 2015 that partially covered patents published in the early of 2015. Second, because our sample uses the priority year of patent, this causes the shift the observed period of patents 1 to 4 years earlier. It also partially explains why the number of French patents decreasing in the years of 2015, 2014, 2013, 2012 and 2011. We decide to cut off our observed years until 2013 due to the skewness of patent data.

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<sup>8</sup> Authors affiliated to a French university, public or private research institution or corporation.

<sup>9</sup> See Appendix 1

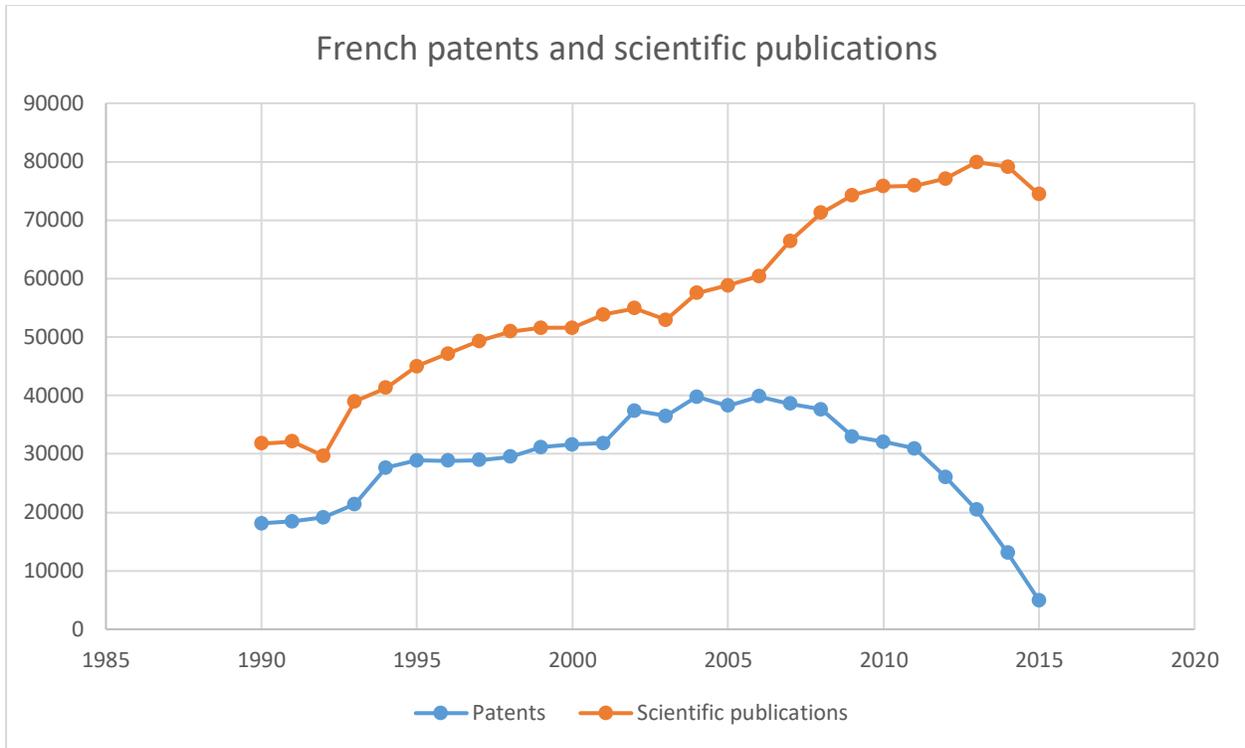


Figure 1. 2: French patents from 1990 to 2015 in PATSTAT patent data (Autumn version 2015)

Generally, we can see the steadily increasing trend of French patents from 1990 to 2007, then it decreases. Therefore, we split the observed period into three phases to analysis regional knowledge expertise in the next sections. The first period is from 1990 to 1999, which is the precedent period of the year 2000 software problem. This period records the highest increasing rate of French published patents, which is a 72% increase. The second period is from 2000 to 2007, which is the precedent period of the global financial crisis. This period shows a 22% increase in published patents. The last period is from 2008 to 2013.

Similarly, there is an increasing pattern of scientific publications. In the first period of 1990-1999 and the second period of 2000-2007, there are 62% and 28,8% increase in publications respectively. In the last period from 2008-2013, while there is a decrease in patenting activities,

the publications still increase at 12,2%. However, the rate of increase in scientific publications is slower over time.

***Data for the interdependence between different types of scientific and technological knowledge expertise***

Following prior literature, we used non-patent references (NPRs) cited in patent data. Then, we created dyads between each patent and the NPRs cited on the front page of the patent (Ahmadpoor and Jones 2017; Bikard and Marx 2018; Cassiman, Veugelers, and Arts 2018; Fleming and Sorenson 2004; Meyer 2000; Narin and Breitzman 1995). Among the 743,693 patents collected, we found 100,377 patents citing 275,951 NPRs.

NPRs are prior-art citations of various sources, such as books, Internet, or patent granted by the Japanese office that are not necessarily related to scientific work. A simple count of NPRs may be an ambiguous and imprecise measure of the use of scientific references (Cassiman, Veugelers, and Zuniga 2008). To overcome the risk of constructing a noisy dataset, we only selected references of articles published in scientific journals. This is a very conservative strategy since it excludes several scientific sources such as books and conference proceedings. Identifying scientific publications in the list of NPRs is challenging because each information (such as title, journal name, volume and issue number, authors' name, year of publication, etc.) are sometimes missing or, when included, truncated or misspelled. Furthermore, scientific references are recorded as unstructured information often grouped in the same cell, and not necessarily in a systematic order, thus increasing the computational challenge. To exploit such unstructured data, we developed an algorithm using Google scholar search engine to identify and extract the title of the article, the academic journal where the article has been published, the year of publication, and the

geographic location of the authors. We obtained 26,068 patents citing 61,486 scientific articles published in 15,012 academic journals. The dataset helps to construct the linkages between scientific domains and technological fields.

Figure 3 shows that there is an increasing trend for citations across patents and scientific publications. We only look at the period of 1990-2011, which is skewness from 2012-2015 due to the shifted years on the patent data. The number of scientific citations in a patent sharply increase from 1.59 in 1990 to 2.75 in 2011, which represents the 72,8% increase.

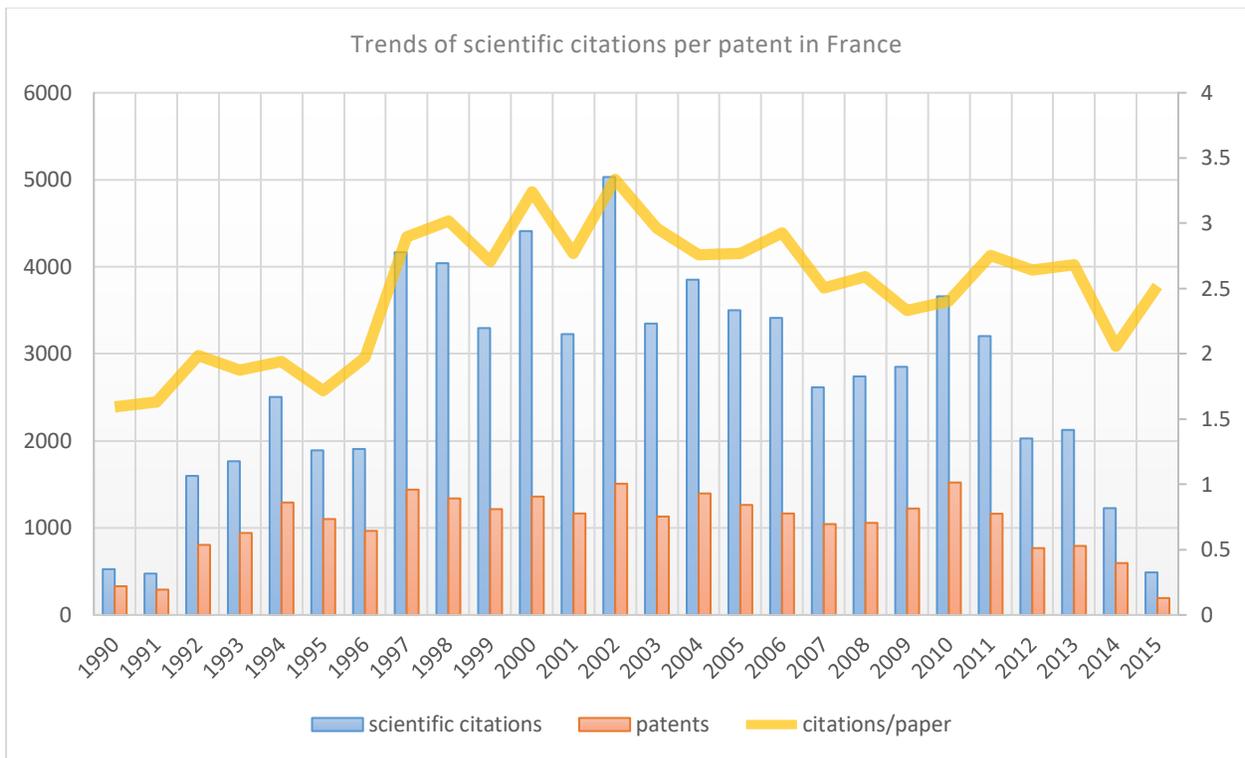


Figure 1. 3: The trend of scientific citations per patent in France (1990-2015)

*Measuring variables*

To smoothen the trend of variables, we sum their value over the past five years to calculate the regional yearly variables. Then, these aggregated values are used to construct individual variable

in year  $t$  in a region. For example, the number of publications in the domain ( $j$ ) in year  $t$  in a region is:

$$P_{j,t} = \sum_{t=0}^{t=4} P_{j,t-1} \quad \text{where } t = \{1994, \dots, t, \dots, 2013\} \quad (1)$$

### ***Regional knowledge expertise variables***

As our arguments about regional knowledge in section 2, this chapter refers to the regional scientific and technological knowledge expertise rather than knowledge bases.

We use the well-known relative –or revealed- comparative advantage that has been used to measure technological expertise (Archibugi and Pianta 1994; Malerba and Montobbio 2003) or national product specialization in international trade (Dalum 1999; Hausmann and Hidalgo 2011). This variable indicates for every region the relative share of forward citation in a specific domain compared to the share of total forward citations in this domain at the national level. More precisely, the technological expertise of region  $r$  is measured as follows

$$RTE_{ir} = \frac{\sum P_{ir} / \sum P_r}{\sum P_{iN} / \sum P_N} \quad (2)$$

where  $P_{ir}$  is the total forward citations that the technological field ( $i$ ) receive within 5-year in the region ( $r$ );  $P_r$  is total forward citations that the region ( $r$ ) receive within 5-year since that technology ( $i$ ) existed in the region;  $P_{iN}$  is total forward citations of the technological field ( $i$ ) receive within 5-year at the national level, and  $P_N$  is total forward citations in France.

We further follow the same logic (as  $TRE$ ) to calculate the regional expertise in each scientific domain ( $RSE$ ). This variable indicates for every region the relative share of scientific

publications in a specific domain compared to the share of publications in this domain at the national level. More precisely, the scientific expertise of region  $r$  is measured as follows

$$RSE_{jr} = \frac{\sum P_{jr} / \sum P_r}{\sum P_{jN} / \sum P_N} \quad (3)$$

where  $P_{jr}$  is the total number of scientific publications in the domain ( $j$ ) in the region ( $r$ );  $P_r$  is the total number of scientific publications in the region ( $r$ );  $P_{jN}$  is the total number of French publications in the domain ( $j$ ); and  $P_N$  is the total number of publications in France.

***The interdependence between different types of scientific fields and technological domains at the national level***

The *interdependence* variable proxies for the degree interplays between science and technology. The level of interdependence between each couple of technological field ( $i$ ) and scientific domain ( $j$ ) is captured by the indicator  $\lambda_{ij}$ , which can be estimated by parametric measures. In a parametric setting, it is assumed that the random combination between ( $i$ ) and ( $j$ ) follows the hypergeometric distribution.

$$\lambda_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}, \quad \lambda_{ij} \in R \quad (4)$$

Where  $J_{ij}$  is the actual number of observed co-occurrences between technology ( $i$ ) and scientific field ( $j$ );  $\mu_{ij}$  is the expected (mean) value of a random technological co-occurrence and  $\sigma_{ij}$  is the standard deviation. Thus, if  $J_{ij} > \mu_{ij}$ , then technology  $i$  and scientific domain  $j$  are highly

related. Conversely, when  $J_{ij} < \mu_{ij}$ , then i and j are relatively independent. We normalize  $\lambda_{ij}$  to be bounded between 0 and unity for consistent comparison across regions.

$$\lambda'_{ij} = \frac{\lambda_{ij} - \text{Min}\lambda_{ij}}{\text{Max}\lambda_{ij} - \text{Min}\lambda_{ij}} \quad (5)$$

## **Empirical analysis and results for French regions**

Since the knowledge production is a cumulative and path-dependent process (Dosi 1982; Nelson and Winter 1982), the process of learning and knowledge creation of inventors in the region is also cumulative and path-dependent (Boschma, Balland, and Kogler 2015; Boschma, Heimeriks, and Balland 2014). Therefore, there are several notes relating to the variables.

First, the RSE, RTE indices and the interdependence are constructed in 5 years-window moving to avoid the truncation bias. For instance, the RSE in the year 1994 and are aggregated from 1990 to 1994 and from 1991-1995 respectively. Even we construct different types of regional scientific and technological indices; we map the overall regional bases by using the average value of all kinds of knowledge expertise (figure 4 and 7 below). We split the sample into three periods to observe the dynamics of regional knowledge expertise over time. Last, we observe the pattern of the relationship between types of science and technology at the national level<sup>10</sup>.

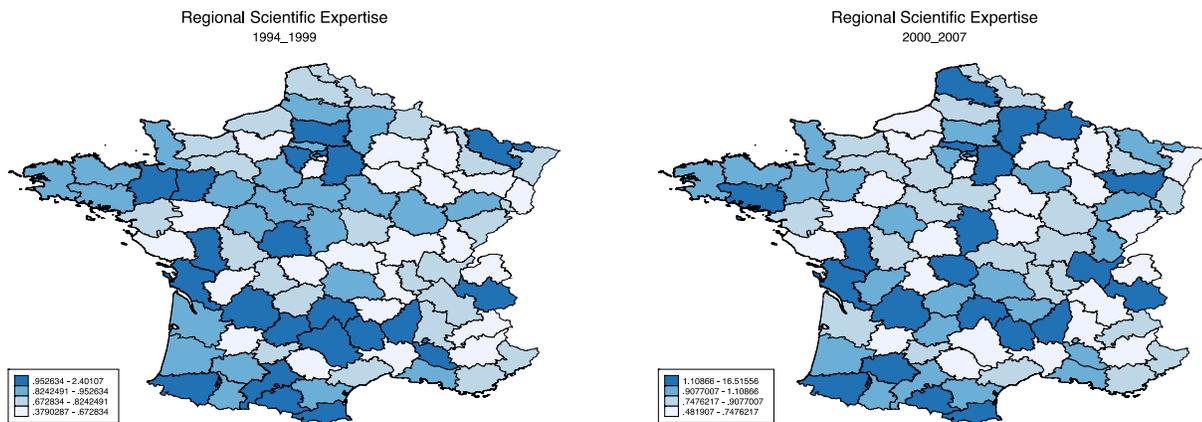
### *Regional scientific expertise*

We apply the threshold of location quotient (LQ), which is a classical technique in economic geography (MacLean and Voytek 1992). This technique generally compares whether a

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<sup>10</sup> We may observe this relationship at the regional level. However, it is out of the scope of this study. We will address this matter in the discussion section.

particular industry in a local economy has a smaller or larger presence compared with the corresponding national economy, which is measured by total employees in the focal industry. In this chapter, we compare knowledge expertise rather than industry specialization. The RSE of a region above one implies the strong scientific expertise<sup>11</sup>, whereas the region does not has specific expertise if its index is below one. Figure 4 shows the dynamic change of regional scientific expertise from 1994 to 2013. The evolution reflects not only the change of the structure of regional science but also the relative change at the national level. It indicates that regions specialize in the specific science fields that they are good at, which those indices are above one. Besides, the regions increasingly specialize in their core scientific fields over time. In particular, the numbers of the region have scientific expertise index greater than one are increasing, which are 21, 33 and 43 in the first, second and third periods respectively. These findings also support the hypothesis that the evolution of scientific knowledge in the region is related to the existing knowledge base (Boschma et al. 2014)



<sup>11</sup> The other study applies a different threshold value of location quotient (LQ) as a sign of strong regional specialization (Martin 2012).

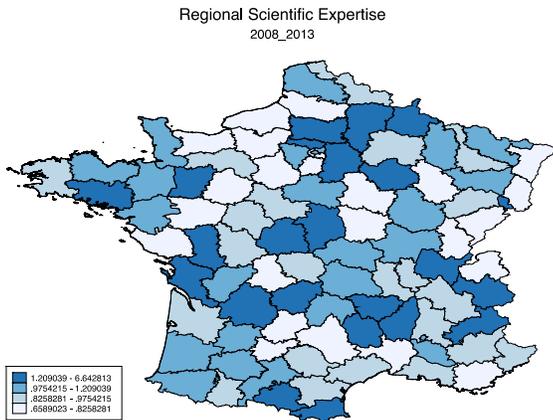
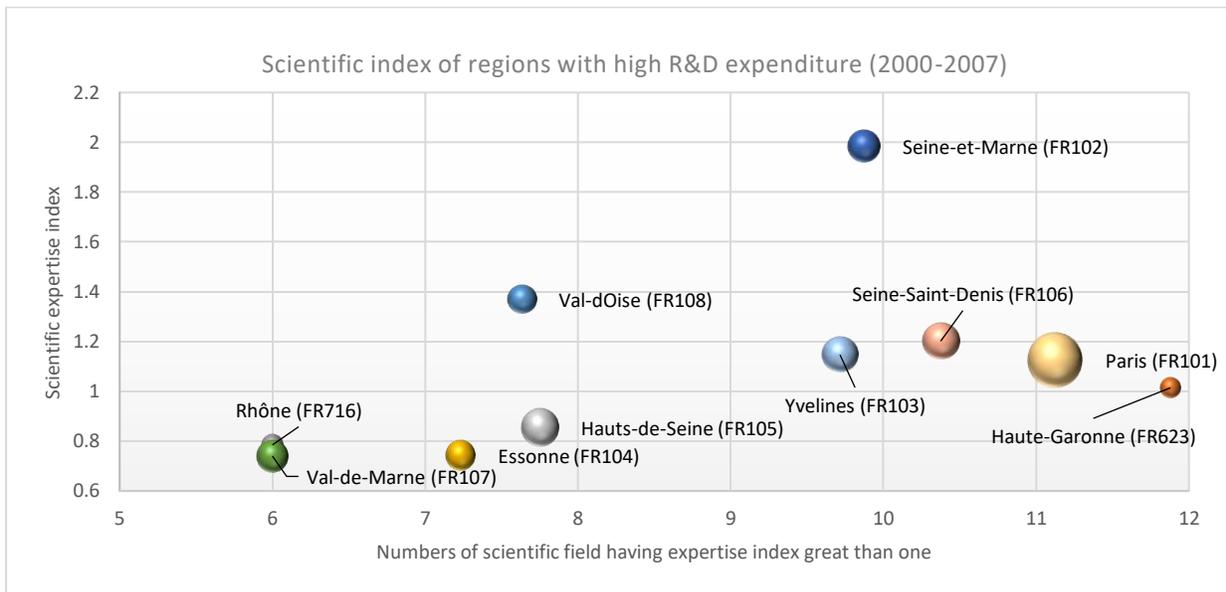
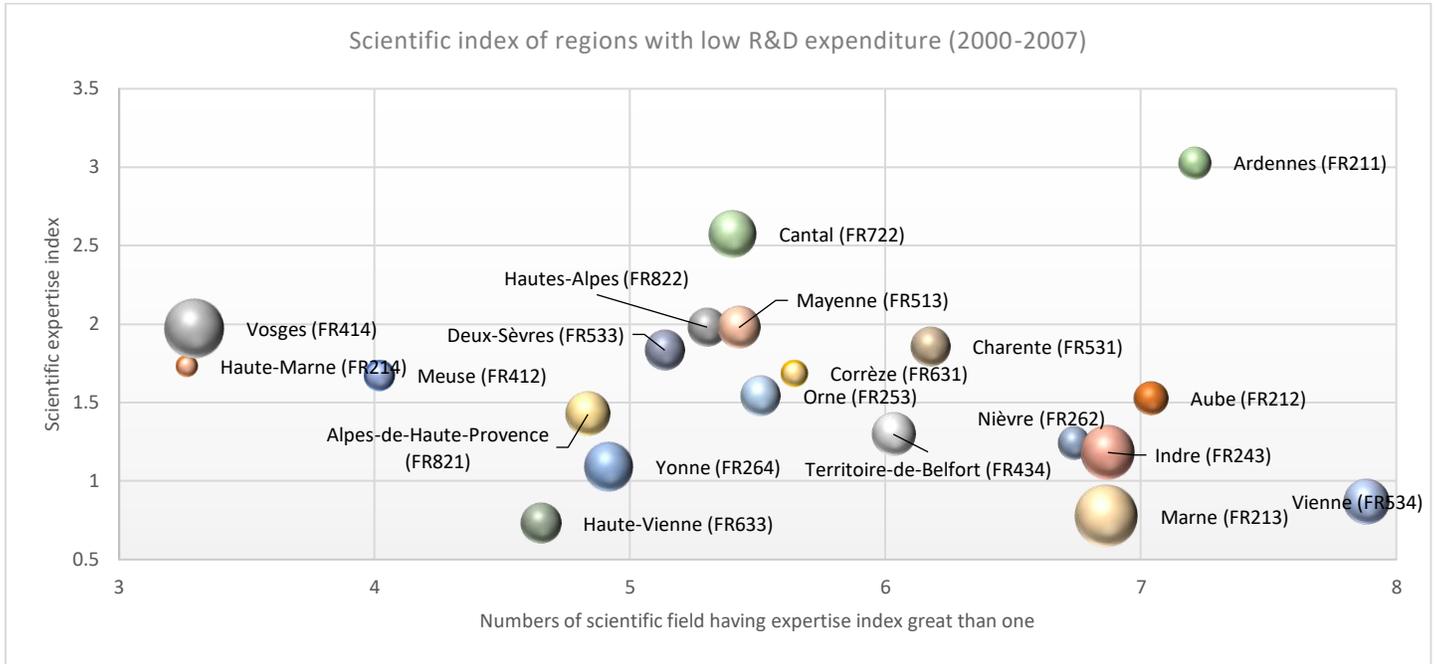


Figure 1. 4: The average of regional scientific expertise of regions (1994-2013)

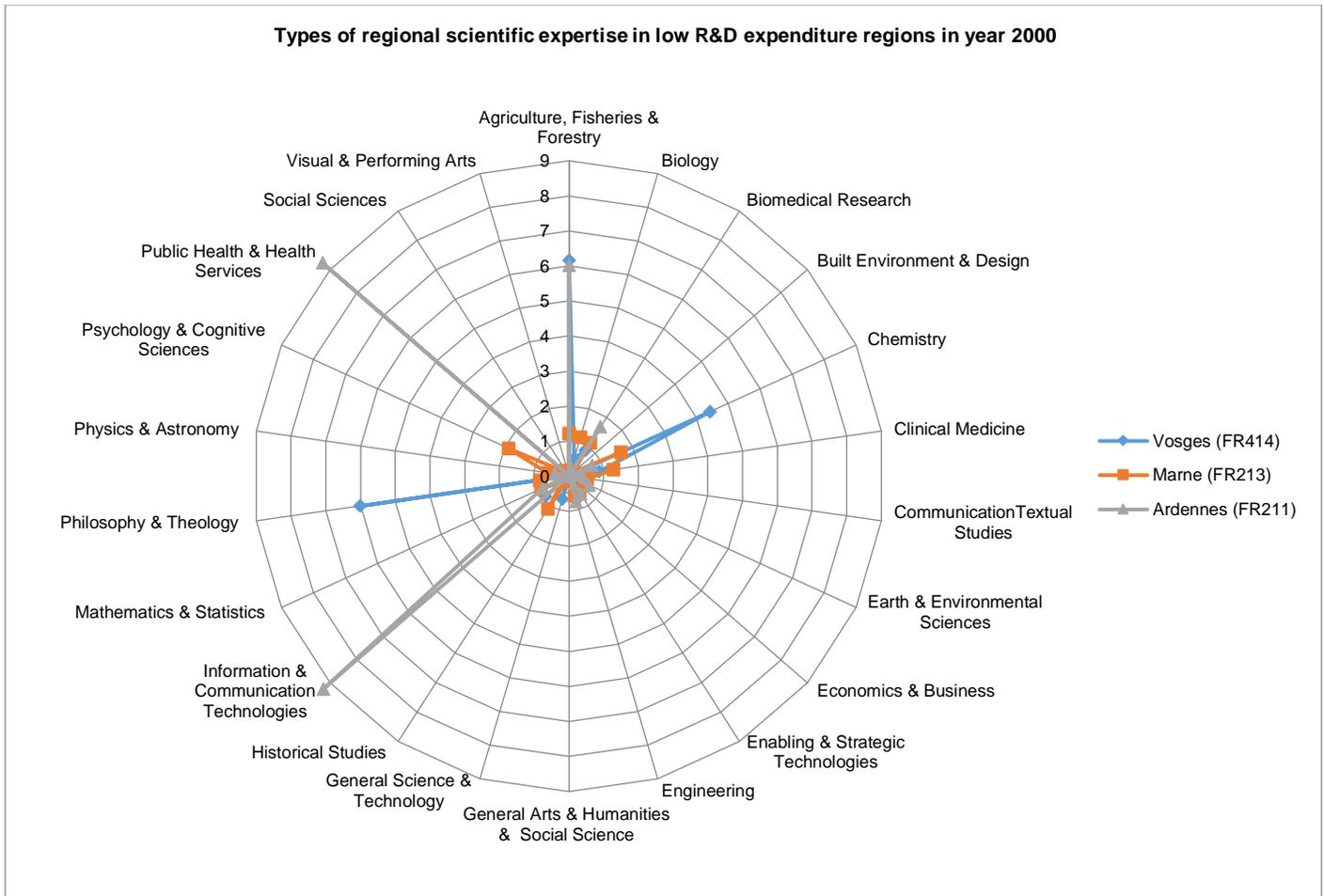
The question is about whether numbers of regional knowledge expertise relates to their R&D expenditure. To answer the above question, we use the sample of the second period (2000-2007). However, due to available data of R&D expenditure at NUTS2 level, we calculate R&D expenditure at NUTS3 level by share of the regional population at the aggregated NUTS2 SOURCE OF DATA: Eurostat, 2019). A region with a larger population will take a larger share of R&D expenditure. Then we average R&D expenditure of regions over the period. We slit regions into three groups, such as low R&D expenditure regions (less than 100 million euros per year), medium R&D expenditure regions (yearly R&D expenditure ranges more than 100 to smaller than 1,000 million euros), and high R&D expenditure regions (greater than 1,000 million euros). Figure 5a, b, c depict relative relationship across R&D expenditure, average RSE index and the number of the scientific fields having expertise index higher than one in the region. Size of the bubble indicates the value of annual R&D expenditure of the region, which is the average value of regional R&D investment from 2000 to 2007. The larger size means that the focal region spends much R&D expenditure compare with other regions. These figures show that the amount of R&D expenditure has a positive relationship with the numbers of the scientific expertise field.

In particular, numbers of expertise fields are about 5 to 7, 5 to 8, and 7 to 11 for the low, medium and high R&D expenditure regions respectively.

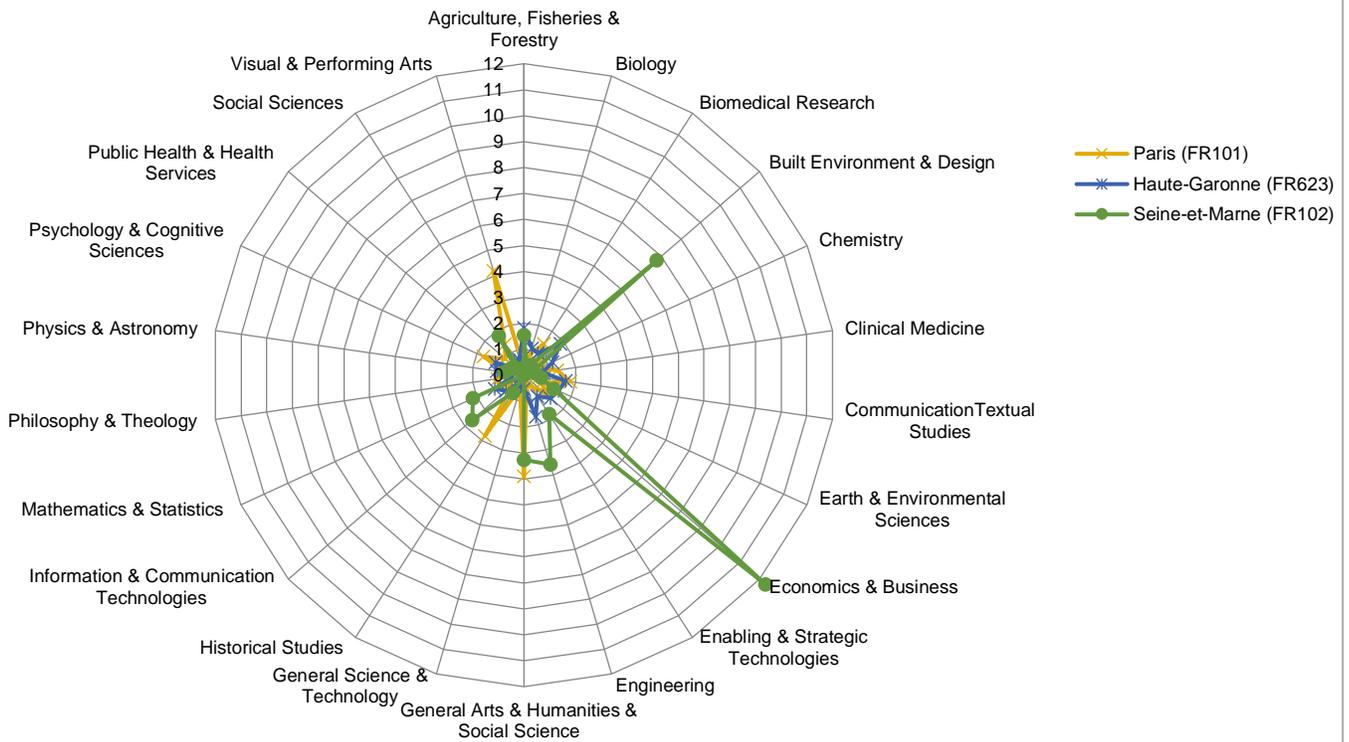




Further, we ask whether R&D expenditure also affect levels of expertise. Therefore, we analysis some groups of regions to understand how different levels and types of expertise fields occurred in regions in 2000 (Figure 6a, 6b, 6c).



**Types of regional scientific expertise high R&D expenditure regions in year 2000**



**Types of regional scientific expertise medium R&D expenditure regions in year 2000**

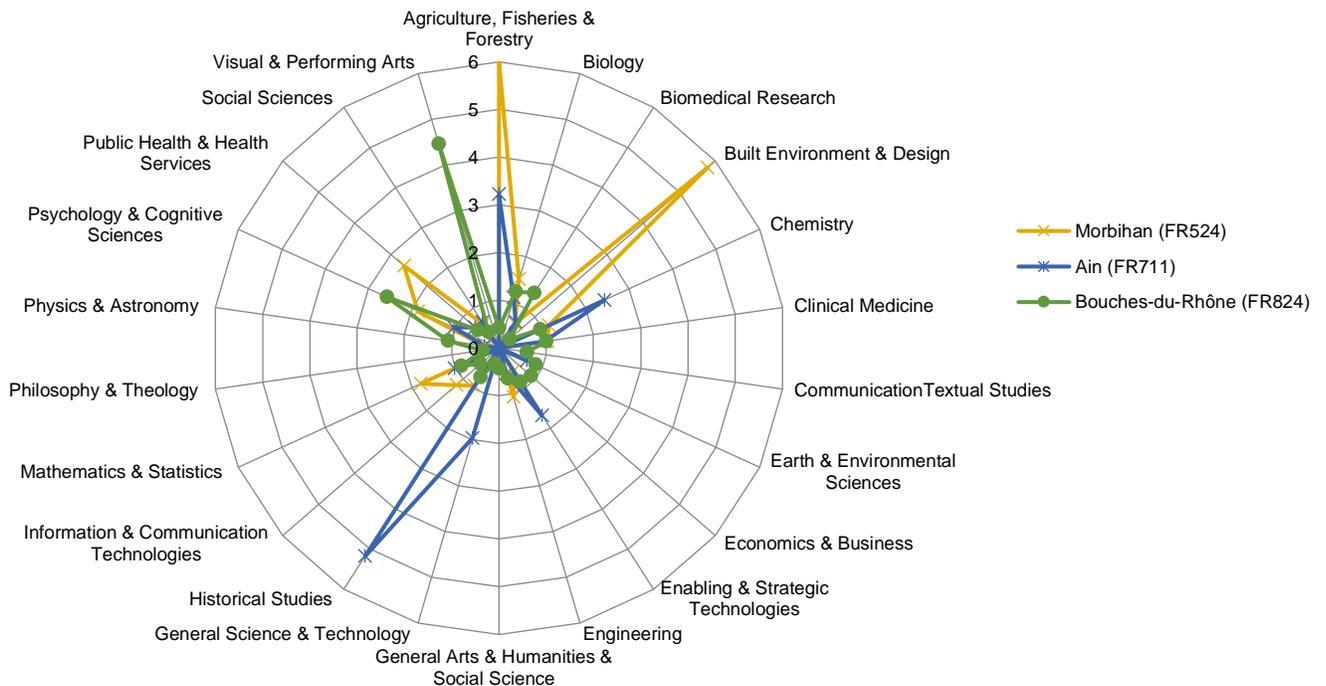


Figure 1. 6 (a, b, c): The scientific expertise of regions in 2000

Figure 6a compares regions with equivalent and different R&D expenditures. The results depict various types of scientific expertise of Vosges, Aube and Ardennes departments. While Vosges and Marne have the most equivalent amount of R&D expenditure of 92,73 and 98,51 million euros per year, respectively, they differently expose at numbers of scientific field gaining expertise. In particular, Vosges department has remarkably achieved a high level of expertise in the science of agriculture, fisheries and forestry (RSE = 6.16); philosophy and theology (RSE = 4.42); chemistry (RSE = 6.00); the others are negligible. Marne department diversifies into the various scientific fields, which has seven scientific fields with expertise index higher than one. Even R&D expenditure of the Ardennes department is about 50,5 million euros, both average RSE index and numbers of scientific fields are high compared with Vosges and Aube. The region actively engage into eleven fields and achieve at extremely high level of expertise at four fields such as agriculture, fisheries and forestry (RSE = 6.02); biomedical research (RSE = 1.67); information and communication technologies (RSE = 9.26); and public health and health services (RSE = 9.28). The findings show that the region may specialize in certain scientific domains or diversify into a different set of sciences.

Further, we investigate whether the amount of R&D investment relates to the level of regional scientific expertise (Figure 6b and 6c). First, we compare the group of high R&D expenditure such as Haute-Garonne, Seine-et-Marne and Paris with 1,037, 1,608 and 2,787 million euros investments in 2000 respectively. Figure 6b shows that Haute-Garonne, which has the lowest R&D expenditure within the group, diversify and achieve expertise at twelve scientific fields. Paris department also gains eleven fields. However, the value of RSE indices of Paris is much higher than those in the Haute-Garonne region (i.e. science in visual & performing art RSE = 4.19 and 0.62, in general arts & social science RSE = 3.89 and 0.53 for Paris and Haute-Garonne

respectively). Seine-et-Marne department is only active in nine-teen fields but has expertise in ten fields. Especially, this region has RSE indices that are higher than in Paris (i.e. science in built environment & design RSE = 6.74 and 0.60, in engineering RSE = 3.57 and 0.38, in information & communication technology RSE = 2.63 and 0.57 for Seine-et-Marne and Paris respectively). They comprise of science in agriculture, fisheries and forestry; built environment and design; earth and environmental sciences; economics and business; enabling and strategic technologies; engineering; information and communication technologies; mathematics and statistics; social science.

Regarding the group of medium R&D expenditure regions, Morbihan department invests about 255 million euros for R&D activities with sixteen fields actively. However, the region has high RSE indices such as agriculture, fisheries and forestry (RSE = 6.01); built environment and design (RSE = 5.77); public health and health services (RSE = 2.63). Ain department has eight on fifteen fields that have RSE indices higher than one. This factor makes the region have high average RSE index and a large number of expertise fields. Even the Bouches-du-Rhone department with the largest amount in R&D investment within the group chooses to diversify into all scientific fields, and there are only six out of twenty-two fields having RSE values higher than one.

### *Regional technological expertise*

Figure 7 displays the evolution of the technological expertise of regions from 1994 to 2013. The structure of technological expertise has gradually changed. The distribution across regions is more balanced than for the scientific expertise because the number of regions with RTE index greater than 1 is larger. However, the trend of specializing decreases over time, which is reverse to the trend of scientific knowledge. In particular, there are 64, 62 and 18 regions with a

technological index greater than one, which is correspondent to the first, second and third periods respectively. The finding indicates that regions may diversify their technological domains, which reduce the expertise index.

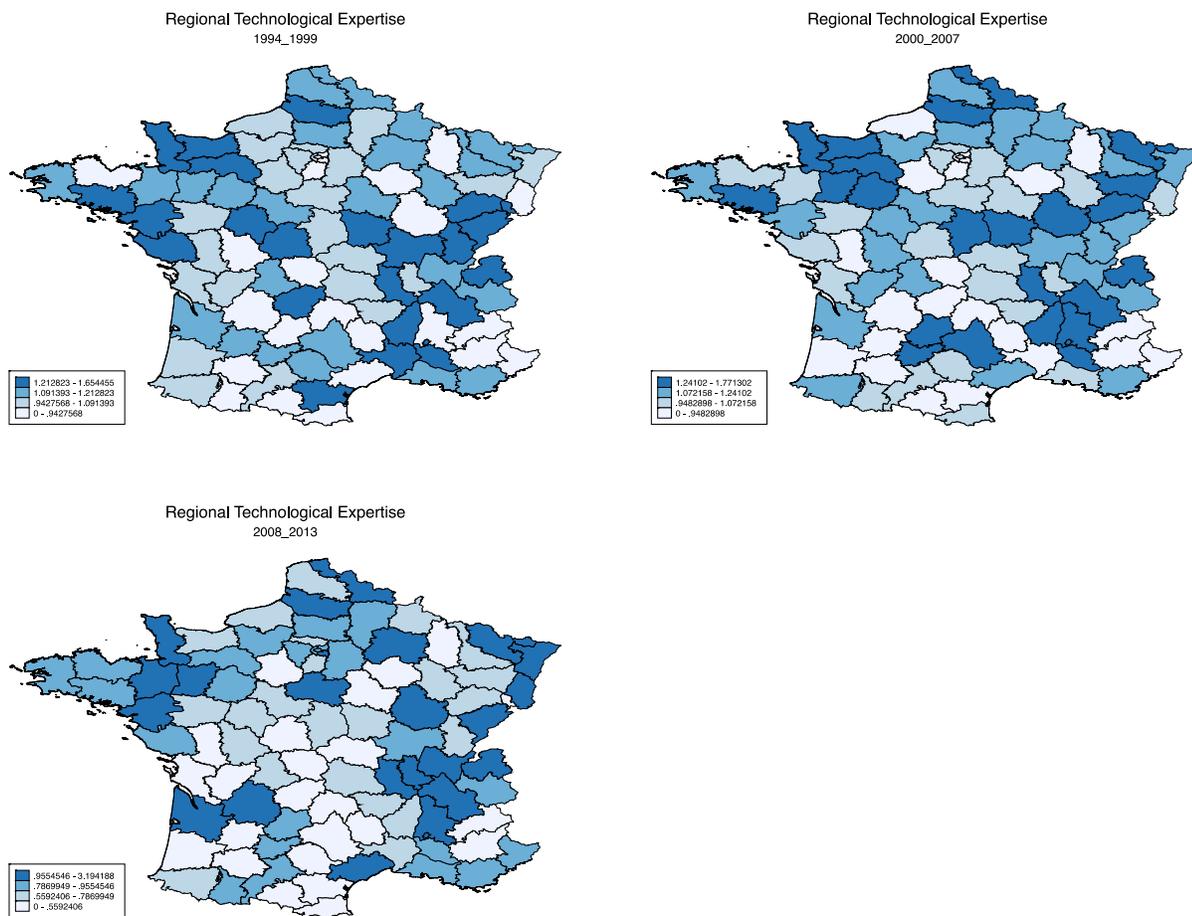
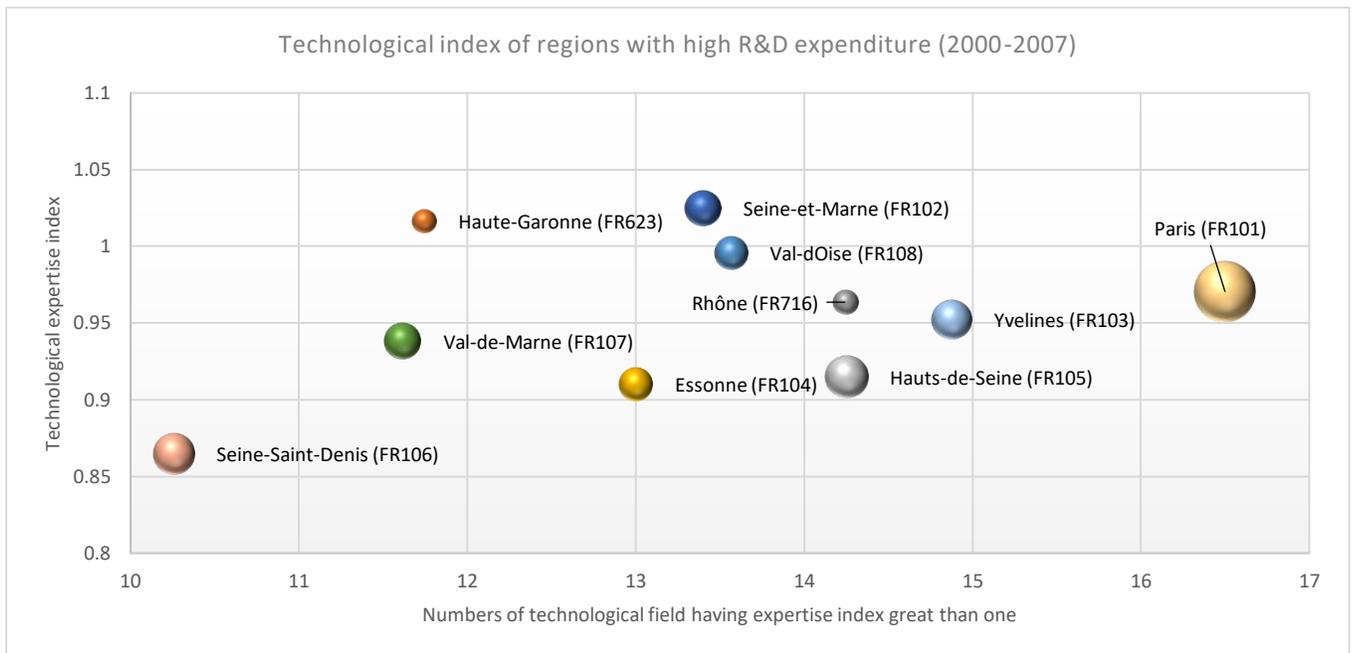
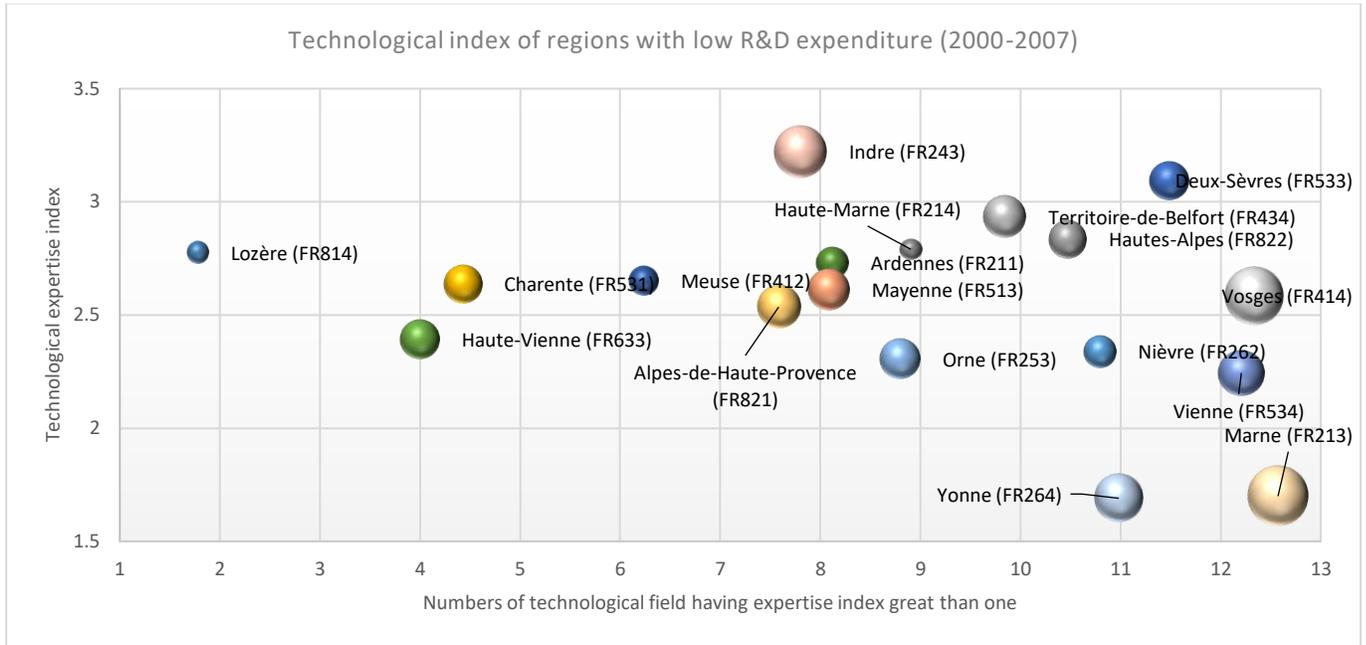


Figure 1. 7: The average of regional technological expertise of regions (1994-2013)

In the same question of the relationship between regional R&D expenditure and a number of expertise fields, figure 8 (a, b, c) displays graphs of average RTE indices, R&D investment, and the number of scientific fields having index greater than one. Different levels of regional R&D expenditure group these figures. The figures indicate that R&D expenditure also has a positive relationship with the number of technological expertise fields. In particular, there are about 4 to

12, 9 to 15 and 10 to 17 technological expertise domains in the low, medium and high R&D expenditure respectively.



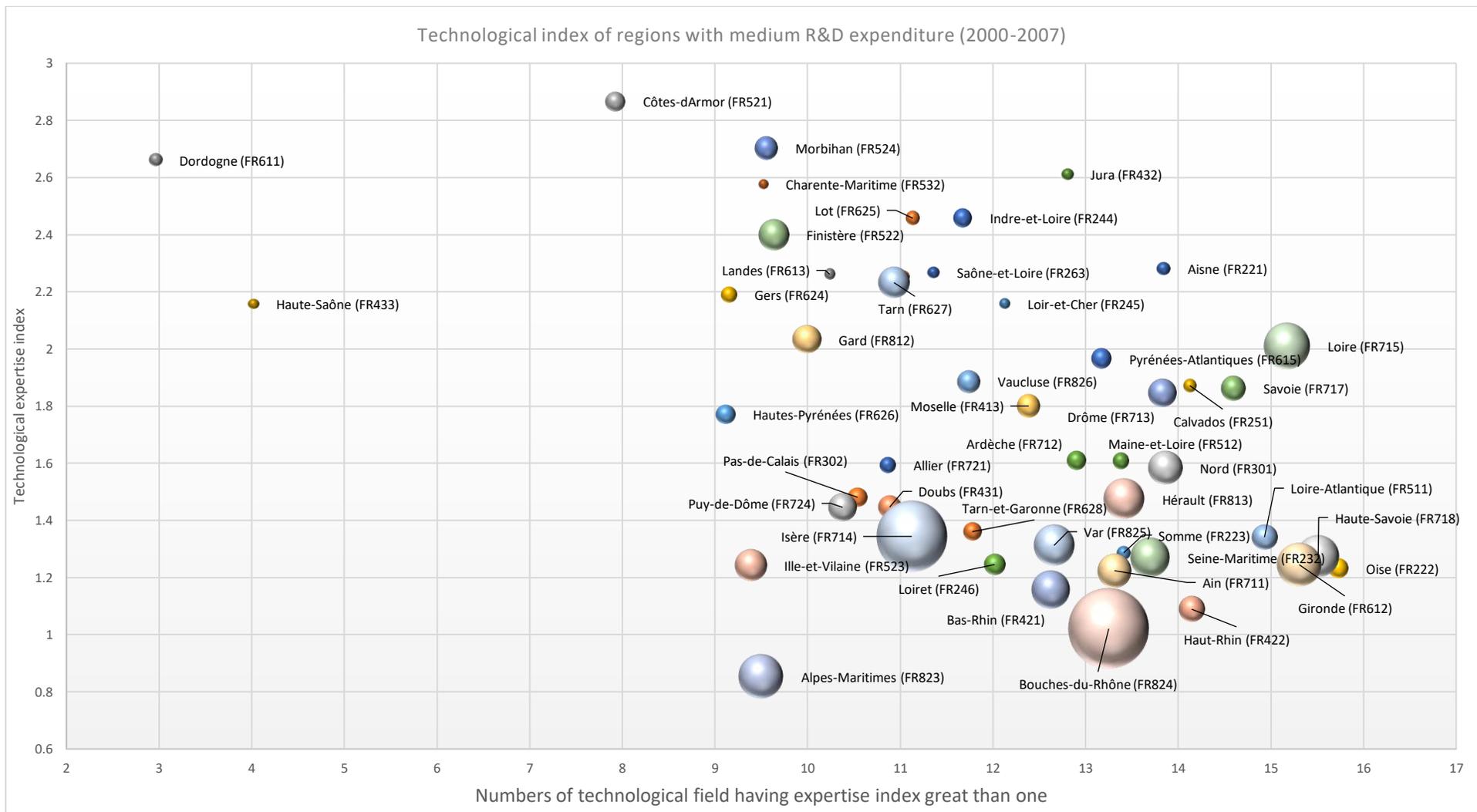


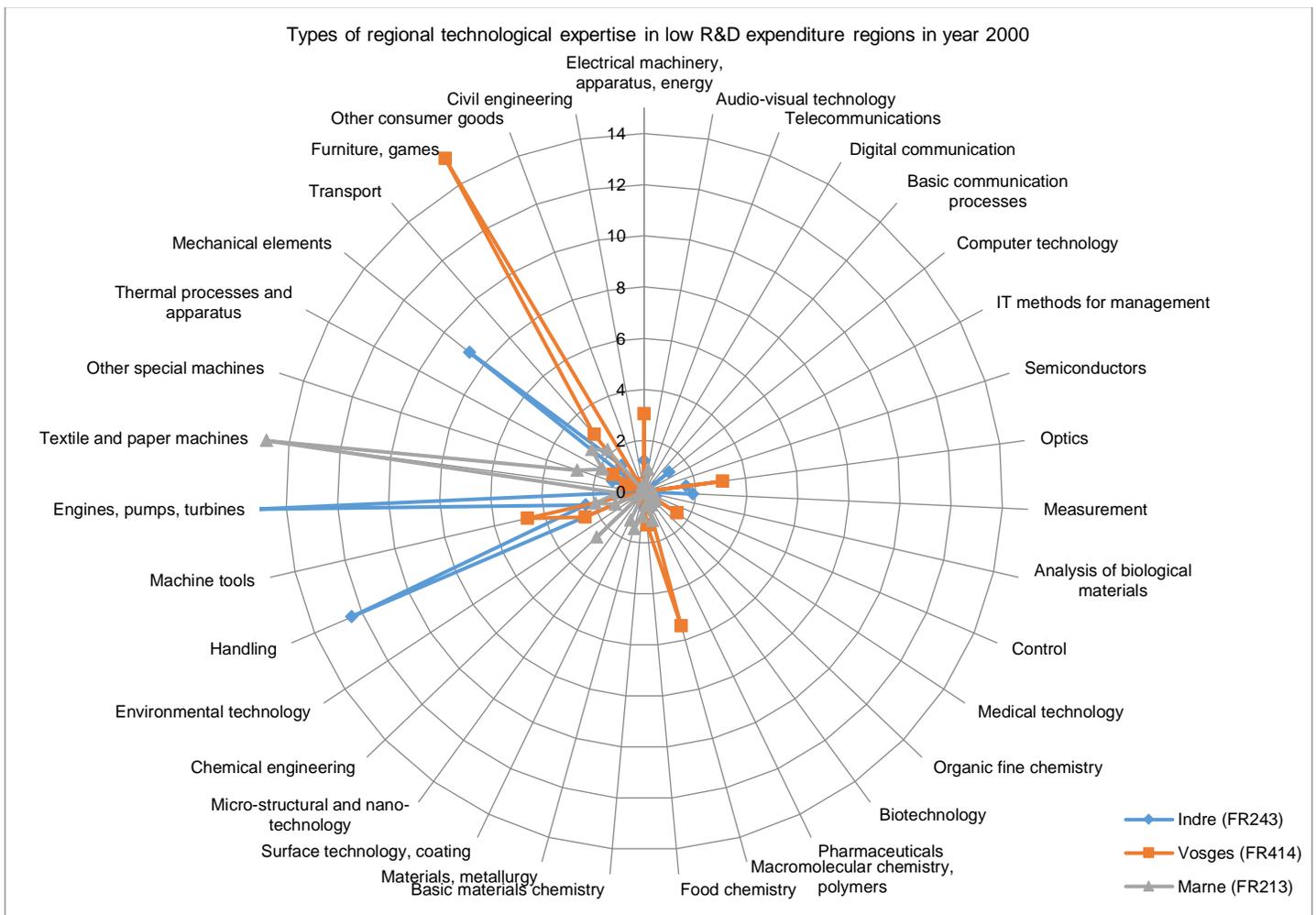
Figure 1. 8 (a, b, c): The average of regional technological expertise of regions (2000-2007)

However, we are also interested in how different levels of R&D expenditure relate to regional technological trajectories. Therefore, we further analysis some groups of regions in the year 2000 to understand how they diversify their technologies (Figure 9a, b, c).

Figure 9a asks whether regions with the same R&D expenditure expose similar average RTE indices and numbers of expertise technologies. We analysis three regions that invest highly equivalent R&D amount in the group of low R&D expenditure such as Indre, Vosges and Marne departments at 83, 92 and 96 million euros respectively in 2000. These regions exhibit different strategies in their expertise in technological fields. While Indre and Vosges regions are quite good at all technological domains they are investing, Marne department diversifies into different technologies. In particular, nine out of eleven and ten out of fourteen technologies gain a high level of expertise in Indre and Vosges regions, respectively. Remarkably, Indre has extremely high RTE indices at their core technologies such as handling (RTE = 12.42); engines, pumps, turbines (RTE = 15.28); mechanical elements (RTE = 8.74). Vosges are good at technologies of electrical machinery, apparatus, energy (RTE = 3.05); optics (RTE = 3.07); macromolecular chemistry, polymers (RTE = 5.43); machine tools (RTE = 4.68); furniture, games (RTE = 15.17). Marne has twelve out of twenty-five expertise technologies. However, the levels of RTE indices are relatively medium such as chemical engineering (RTE = 2.57); machine tools (RTE = 1.96); other special machines (RTE = 2.75); mechanical elements (RTE = 2.64); transport (RTE = 2.17).

We ask the above question to the group of high R&D expenditure regions. Val-de-Marne, Yvelines and Seine-Saint-Denis invest 1,641, 1,782 and 1,872 million euros in R&D activities in 2000. We find that average RTE indices and numbers of expertise fields are relatively similar at the aggregated level (figure 8b). However, if we study at the fine-grained level of each field, results

are heterogeneous across regions. Yvelines region is good at most technologies they are actively, particularly nine-teen out of thirty-four domains have RTE indices higher than one. In the same vein, Val-de-Marne and Seine-Saint-Denis have nine out of thirty-five and twelve out of thirty-one expertise fields respectively. In addition, while most of RTE indices are just higher than one, some technologies expose high level of expertise such as micro-structural and nano-technology (RTE = 4.74) in Val-de-Marne; textile and paper machines (RTE = 2.30) and thermal processes and apparatus (RTE = 2.22) in Yvelines; audio-visual technology (RTE = 3.82) and mechanical elements (RTE = 2.48) in Seine-Saint-Denis. The results imply that these technologies play an important role in their regional knowledge bases.





In figure 9c, we ask whether regions with different levels of R&D expenditure exhibit similar levels of technological expertise. In particular, Calvados, Savoie and Loire regions invest in R&D activities at 140, 264 and 502 million euros in 2000 respectively. These regions have as same as average RTE indices (i.e. 1.87, 1.86 and 2.00) and numbers of technological expertise domains (i.e. 14, 15, 15). Loire regions have ten out of twenty-four expertise technologies, especially several files achieve high levels of RTE such as measurement (RTE = 3.96); handling (RTE = 5.50); machine tools (RTE = 6.23); transport (RTE = 2.85); furniture, games (RTE = 14.41); other consumer goods (RTE = 2.51). In a similar comparison, Savoie and Calvados have six-teen out of twenty-six and eleven out of twenty-nine expertise technologies respectively. Notably, Savoie region exhibits high levels of expertise in materials, metallurgy (RTE = 5.93); handling (RTE = 3.39); machine tools (RTE = 3.17); textile and paper machines (RTE = 2.62); other special machines (RTE = 3.17). Besides, Calvados is good at computer technology (RTE = 2.01); IT methods for management (RTE = 2.41), semiconductors (RTE = 2.69); food chemistry (RTE = 9.48); surface technology, coating (RTE = 2.55); furniture, games (RTE = 8.96). The findings show that regions may heavily invest in their core sets of technologies, thus become experts in those fields.

In sum, regional knowledge bases are too broad to capture specific types of regional expertise. Regional knowledge expertise at a more fine-grained level can give more insights on how regional knowledge is created and cumulative.

*The interdependence between different types of science and technology at the national level*

We use VOSviewer to depict the relational network of scientific fields and technological domains (at the national level). The network includes nodes, which represent both scientific fields (sc1, sc2,...,sc21) and technological domains (T1, T2,..., T35) (Figure 10). The size of

the node presents the weight of science or technology observed during the period. The higher the weight of an item is, the larger the circle of the item is. The colour of an item is determined by the cluster to which the item belongs to. The citation between a patent and a scientific publication, which represents the relationship between science and technology, is depicted as a link. The short distance between nodes implies that they cite or are cited together. The strong link (thick line) indicates that many repeated connections are observed.

We also split into three observed periods, which are correspondent with those of regional scientific and technological expertise. Figure 10 reveals that the dynamic relationships between science and technology changing over time<sup>12</sup>. In particular, in figure 10a, there are five clusters of science and technology. The most frequency cited fields of science, which the sizes of the node are large, are information and communication technologies (S\_14); engineering (S\_11), public health and health services (S\_19); enabling and strategic technologies (S\_10); physics and astronomy (S\_17). The biggest cluster, where the number of nodes is large, is comprised of science in mathematics and statistics (S\_15); philosophy and theology (S\_16); psychology and cognitive sciences (S\_18); social sciences (S\_20). The second large cluster is consist of science in agriculture, fisheries and forestry (S\_1); biology (S\_2); biomedical research (S\_3); chemistry (S\_5); and clinical medicine (S\_6).

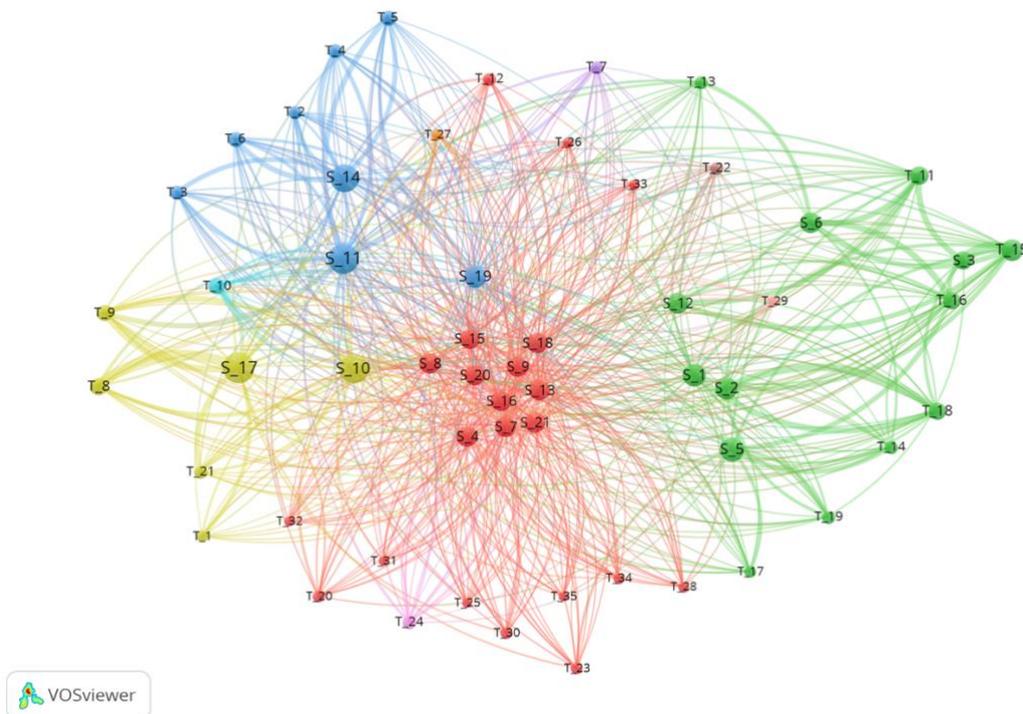
In the second period (2000-2007), the structure of interdependence between science and technology changes and separates into three notable clusters of nodes (figure 10b). The cluster of science in information and communication technologies (S\_14); engineering (S\_11) is combined to the biggest cluster in the first period, which make it bigger in terms of the number of nodes. As a result, the industrial technologies in audio-visual technology (T\_2); telecommunications (T\_3); digital communication (T\_4); basic communication processes

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<sup>12</sup> Only the relationship between nodes having more than 100 linkages are displayed.

(T\_5); computer technology (T\_6) also join this cluster. Science in chemistry (S\_5) is more cited and cluster to technology in organic fine chemistry (T\_14); macromolecular chemistry and polymers (T\_17); basic materials chemistry (T\_19).

In the last period (2008-2013), the position of cluster science in enabling and strategic technologies (S\_10); physics and astronomy (S\_17) shifts to the center of the network. This cluster gravitates toward science in general science technology (S\_12); agriculture, fisheries and forestry (S\_1); earth and environmental sciences (S\_8); engineering (S\_11). The big size of nodes in enabling and strategic technologies (S\_10); engineering (S\_11); physics and astronomy (S\_17) indicates that they are the most cited by industrial technologies (Figure 10c).



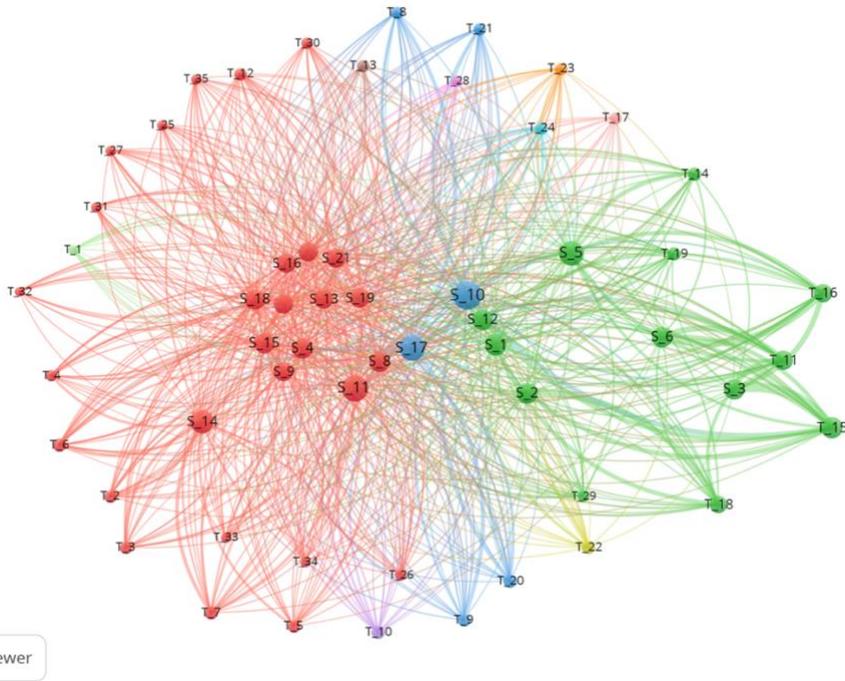
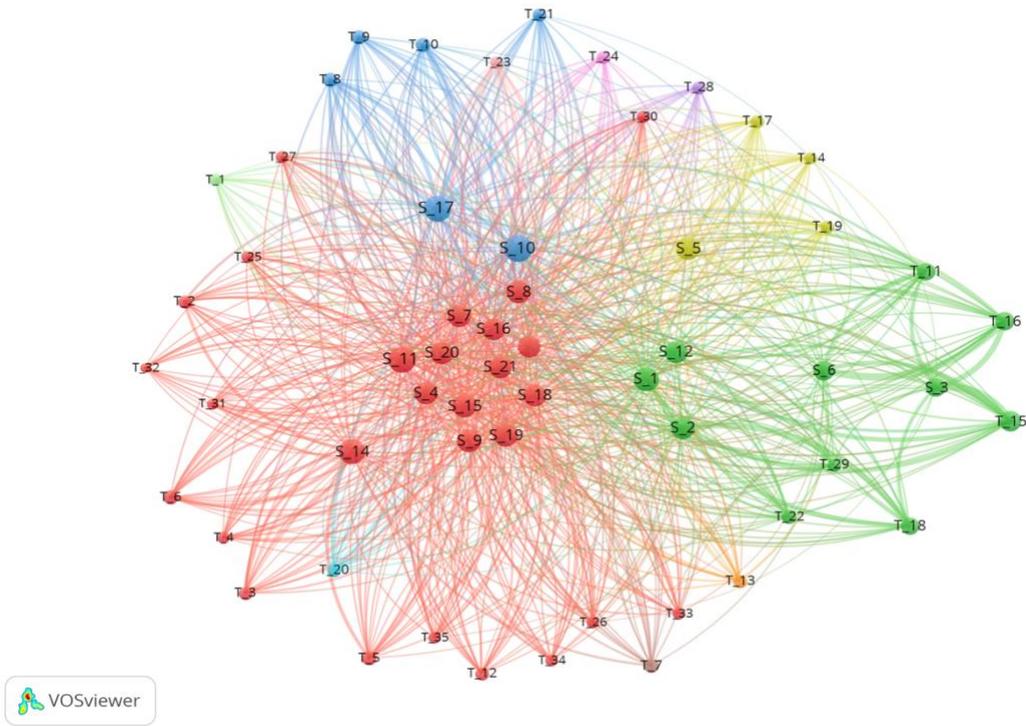


Figure 1. 10 (a, b, c): The interdependence between different types of national scientific and technological expertise

Blazek and Kadlec (2019) show that the West European regions are well integrated between R&D systems. That is the highest share of scientific publications, which are co-

authored by academic scientists and industrial inventors, compared with the Southern, Central, and Eastern European regions. This fact implies the mutual interaction across science and technology in the West European regions. Therefore, at the fine-grained analysis, particularly in French regions, we want to examine whether the level of interdependence between a particular pair of science and technology (at the national level) relates to regional technology that is correspondent to the focal science. As well known in innovation literature, technological domains that strongly rely on science are more dynamics, which provide inventors more combinational options for their innovation (Audretsch and Feldman 1996; Bikard and Marx 2018; Fleming and Sorenson 2004; Grillitsch, Asheim, and Trippi 2018). Therefore, we may expect that such particular technological expertise in the region will increase.

In order to depict that relationship, we select data about the interdependence of the year 1994. We next slit different levels of interdependence, which range from 0.2 to 1. We also choose the group of regions having equivalent R&D expenditure, which belongs from 500 to 1,000 million euros. Figure 11 displays the relationship between the level of interdependence (at the national level) and technological expertise index (at the regional level). The results reveal that technological expertise index has a positive correlation with levels of interdependence.

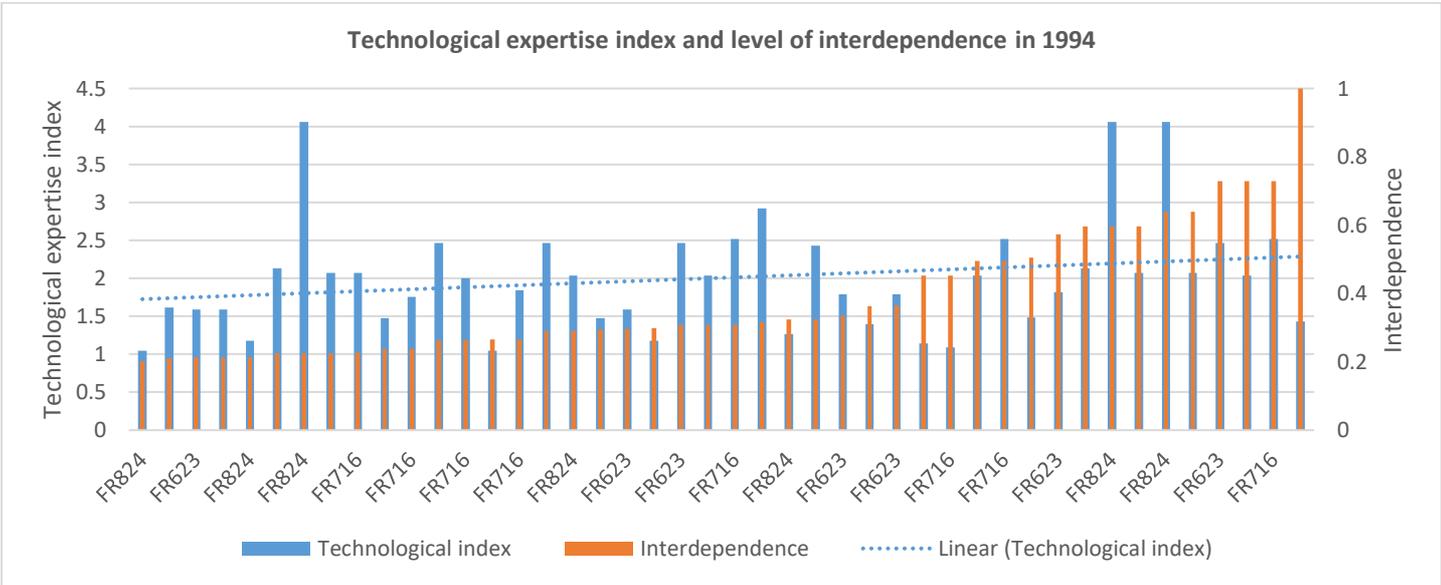


Figure 1. 11: The relationship between interdependence and technological expertise index of regions

## **Discussion and Conclusion**

This study aims to further unpack the regional knowledge bases in the RISs in order to understand how local actors can use and leverage their locally current knowledge expertise. First, we review the theoretical concept of various kinds of regional knowledge bases. We then propose to use a fine-grained level of knowledge bases, namely knowledge expertise, to gain more insights about sources of knowledge. We use French patent and publication datasets to disentangle the process of knowledge creation undertaken by local inventors and scientists. The results exhibit that R&D expenditure has a positive relationship with numbers of the scientific and technological expertise of the region. However, the level of regional expertise index is not related to R&D expenditure. Second, regions are heterogeneous in terms of being expertise in specific types of scientific and technological domains, which are core knowledge bases of the regions. Last, the level of technological expertise will increase if it is highly connected to a scientific field.

The chapter contributes to the current literature in several aspects. First, the findings are consistent with the characteristics of regional knowledge bases, which are cumulative and path-dependent (Asheim and Coenen 2005; Asheim and Gertler 2006; Martin 2012). Second, the results also align with the concept of technological relatedness, which is a potential source for emerging new technology in the region (Boschma et al. 2014, 2015; Frenken, Oort, and Verburg 2007). More than the benefits of relatedness, this chapter shows that the dynamic relationship between each pair of science and technology could provide more fruitful sources of knowledge. Thirdly, we also add to the management literature of innovation generation that inventors can identify, select and combine different elements of scientific knowledge (Ahuja and Katila 2004;

Fleming and Sorenson 2004; Gittelman 2016; Lim 2004; Narin et al. 1997; Nelson 1959). The map of their interdependences could guide them to search for new knowledge.

Building on the method of analysis, one could address further research questions. For instance, one could ask whether a region combining the high level of relatedness of a specific pair of science and technology is more innovative than those regions combining both high and low levels of relatedness across science and technology. How can less-developed regions leverage the distant knowledge sources (either a specific science and/or technology) for their innovation generation? At the microlevel, one may ask whether the pattern of interdependences between science and technology could orient scientists to pay attention to the applied research rather than basic research by studying a specific research direction. In addition, one may examine whether levels of dependence between specific pair science and technology enhance the inventiveness of innovation (in terms of explorative and exploitative). One can assume that an innovation, which combines the high relatedness of technology to the focal innovation and the low relatedness to a specific science field, may create a potential combination. This low relatedness to a specific science implies potentially unexplored combination rather than an unfruitful combination. Therefore, inventors may project their combination search, which helps to reduce risks and costs.

We acknowledge that the process of knowledge creation is complex and hard to be observed by a set of patents and publications. The study aims to provide an overview of various types of knowledge expertise and their dynamic relationships. We suggest to extend and move the scheme of research agenda towards more advanced works relying on regional knowledge expertise.

## **Chapter 2**

### **The Time Value of Local Scientific Expertise**

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## **The Time Value of Local Scientific Expertise**

### **Abstract**

The linkage between science and technological progress has long been argued. In the literature of innovation creation scholars have used the cited publications in the focal patent as a mechanism to explain this general relationship. However, no attention has been given to understand the underlying conditions that accelerate the process of references to scientific publications. Relying on the literature of geography innovation, this paper argues that scientific expertise in the region, which is correspondent to the focal technological innovation, leads inventors to search, identify or verify relevant scientific materials. As a result, this search process also enhances the value of the focal innovation not only to the future direct citing innovation but also to the indirect citing innovations. The impact of the focal innovation on technological progress is entirely captured by the direct count of forward citation and the multi-generational forward citation tree. Empirical analyses of patent data support this thesis.

**Keywords:** geography of innovation, diffusion of knowledge, technological progress

## **Introduction**

The literature has extensively discussed the important role of science in technological development (Arundel and Geuna 2004; Callaert, Grouwels, and Van Looy 2011; Wesley M. Cohen, Nelson, and Walsh 2002; Laursen, Reichstein, and Salter 2011; Patelli et al. 2017; Subramanian and Soh 2010). Innovation scholars not only evidence that science and technologies have always exhibited intimate linked but they also have shown that this connectedness has increased in recent time (Cockburn and Henderson 1998; Hicks et al. 2001; Narin et al. 1997). Science reduces innovation costs by guiding the selection and the development of the most useful paths in complex technological environments (Fleming and Sorenson 2004; Rosenberg 1992; Salter and Martin 2001). Science also provides opportunities to explore new directions. While firms tend to privilege innovative investment in familiar environments with lower uncertainty and higher returns (Fleming 2001), access to science may become useful to overcome the exhaustion of potential opportunities due to the natural limits of the exploitation of familiar technological domains (Ahuja and Katila 2004; Fleming 2001; Fleming and Sorenson 2004). Finally, different studies suggest that science contributes to fasten the innovation process (Mansfield 1991) and to increase the quality of innovation as evidenced by the forward citations premium received by patents originating from universities (Jaffe and Trajtenberg 1996; Mowery and Ziedonis 2002).

However, recent works have highlighted contingencies in science technology relations. Empirical studies using scientific publications referenced in patent documents to link patents to scientific production show that science has higher impact on patents using complex and interdependent technologies (Cassiman et al. 2018; Fleming and Sorenson 2004) and that science matters more for some specific technological fields (Bikard and Marx 2018; Ke 2018). For instance, pharmaceutical or chemical technologies seem to rely on science more than do

other technologies (Harhoff et al. 1999).

Another striking contingency is the spatial determinants of knowledge externalities. Scholars in the geography of innovation have provided evidence that science dissemination is geographically bounded and that proximity with academic research conditions the contribution of science to innovative productivity (Abramovsky, Harrison, and Simpson 2007; Acs, Audretsch, and Feldman 1994; Anselin, Varga, and Acs 1997; Cockburn and Henderson 1998; Feldman 1994; Hall, Link, and Scott 2003; Jaffe, Trajtenberg, and Henderson 1993; Laursen and Salter 2004, 2004; Mansfield 1995; Salter and Martin 2001; Zucker et al. 2002). Science is often described as a public good enabling frictionless diffusion of scientific knowledge (Nelson 1959). Both the norms of publication promoted by scientific communities (Partha and David 1994; Stephan 1996), and the codification of scientific knowledge required for publication facilitate the dissemination of knowledge beyond specific communities, social networks and geographic distance (Sorenson and Fleming 2004). However, the capacity of inventors to benefit from scientific externalities relies on their ability to absorb and exploit knowledge produced by communities of experts. They need to build field-specific competencies to identify, select and integrate relevant knowledge (Cohen and Levinthal 1989). Such absorptive capacities do not only rely on R&D investment because although codified, science is also socially embedded knowledge, produced by communities that have specific norms and logics. Thus, understanding and using knowledge produced by universities often requires being active members of scientific communities or establishing direct links through face-to-face interactions with scientists (Gittelman and Kogut 2003).

Studies interested in the process of knowledge transfer have described the time required for creating these links. Breschi and Lissoni (2001) have shown that science externalities generally rely on formal collaborations based on contractual relations. Analyzing Advanced

Technology Projects Hall et al. (2003) evidenced that such collaborative projects with academics tend to be more difficult than those that do not and generally experience delays. Not surprisingly, although inventors collaborate primarily on top-quality departments of local universities (Laursen and Salter 2004), important scientific articles negatively correlate with high impact patents (Gittelman and Kogut 2003). In the same direction, studies show that the most impactful patents are granted to firms engaged in the production of science through a collaborative agreement with universities but do not cite scientific references (Breschi and Catalini 2010; Cassiman et al. 2018).

The objective of this article is to understand better this geographic dimension in the links between science and technologies. More precisely, the question is to analyze how, and according to which conditions, developing scientific expertise matter for the development of regional innovation capacities.

One could assume that the level of scientific expertise should affect the rate of diffusion because the local science enhances the ability of local inventors to recognize, access and acquire the potential publications that favour for their innovation activities. As a result, it may reduce the time for local inventors to reference to scientific publications. Besides, because inventors can select the valuable and verify their novelty of the innovation, we may expect the value of the innovation higher. Then the above mechanism may also help to explain the diffusion of knowledge across technological innovations.

This study provides evidence on the impact of local science expertise on the rapid diffusion of knowledge. We collect datasets of French patents in the 1990-2013's period to construct the measurement focus on the dyads between patent and scientific (peer-reviewed) publication. We measure the time lag between the published year of cited publications and citing patent to captures the diffusion of knowledge from scientific publication to the invention.

The second model tests the impact of the underlying mechanism on the rate of diffusion of knowledge across technological innovations. French patents are associated with technological classes (WIPO)'s classification to distinguish the different technological groups in our samples. The French scientific papers from 1990-2013 are classified into scientific fields based on the classification of WoS Journal Subject Categories developed by Thomson Reuters. This dataset is used to construct the scientific expertise in the region. Our result shows that the local scientific expertise, which is relevant to the focal technological innovation, decreases the time lag between publication-patent citation as well as increase the future citations received by the focal patent. The results are consistent with the idea that scientific expertise accelerates the diffusion of information between science and technology as well as between technologies. Rather than rely on the published materials claimed in the focal innovation, we examine the antecedent of scientific references reported in the technological innovation. This helps us to explain the mechanisms behind the difference in the time lag between publication-patent links. Therefore, the paper will help scholars to better understand the different mechanisms for the diffusion of knowledge and/or interplay between science, innovation and technological progress.

The paper is structured in five sections. In section 2, the literature is discussed. The third section describes the data collection. The fourth section provides the details of method and measurement. The fifth section presents the results. The implication and discussion are highlighted in the sixth section.

## Literature

### *The diffusion of knowledge in geographical proximity or distance*

The geography of innovation literature has found evidence of geographically localized diffusion of knowledge through high the concentration of industrial cluster (David B. Audretsch & Feldman, 1996; Marshall & Marshall, 1920). The idea emphasizes that the industry-specific knowledge existing in the region provides local firms with significant advantages rather than isolated counterparts. Following Marshall's idea, scholars have empirically examined localized knowledge diffusion.

Jaffe et al. (1993) first tested the concept by using patent-patent citations, which is a proxy of knowledge diffusion. The results show that patent citations are geographically concentrated at the region, states and country levels in the United States. These results are held even after controlling for proximity-concentration of local firms within an industry. In the following study by using patent citation as knowledge flows, Jaffe and Trajtenberg (1996) also report the positive relationship between geographic proximity and citation across patents. This effect decreases with the increasing time lags across patents because the technological advantages created in a region will be disseminated and later used by other regions. The diffusion of knowledge is stronger if the companies locate nearby universities because the proximity strengthens social ties between researchers and inventors, and facilitates technological opportunity.

Even geographical proximity provides a means for information search and coordination; knowledge is not easily contained (Feldman 1999). Therefore, the impact of geography as a mechanism for knowledge diffusion is difficult to disentangle to other mechanisms. In this context, Feldman emphasizes the critical role of individuals as carriers of knowledge. In the

similar vein, other study also argues that the knowledge is deliberately diffused based on the degree of tacitness and the movement of researchers, R&D engineers, and graduates (Breschi and Lissoni 2001). Besides, because social networks are generally geographically localized, knowledge diffusion is also localized. However, this localization does not result from co-location per se, but networks of inventors. In this sense, the diffusion of knowledge may not be entirely localized.

The institutional characteristics of science make the diffusion of knowledge across scientific publication and technological innovation not being geographically bounded. First, rather than inventors, who focus on the particular technological innovation, scientists generally refer to tackle more fundamental problems that can potentially be applied in a broader range (Henderson et al. 1998). Second, the characteristic of “winner-take-all” rewards surrounding first discovery engenders scientists to publish their findings (Merton 1957). Third, the norm of openness of science also offers an effective means to disseminate it to the scientific community because scientists can establish and claim their findings (Merton 1957). Taken together, these scientific institutions promote the diffusion of knowledge widely.

Indeed, a study on publication-patent citation in the Netherland polymer patents shows that, at first, geographic proximity favours localized knowledge diffusion, however, when controlling for self-citation this effect disappears (Heinisch et al. 2016). The evidence indicates that the diffusion knowledge, brought about by scientific publication and technological innovation, are mainly carried out by research collaborations and mobility; thus, co-location per se has little effect.

*Scientific expertise and the rapid diffusion of knowledge across science and technology*

Even the diffusion of knowledge through scientific publications may disperse and has public nature, the main critical task of inventors is either to search the potential source of scientific knowledge or to endorse their technological novelty. The earlier science plays as a mechanism to provide new ideas, and the latter science helps to verify whether the focal technological innovation is relevant to the scientific discoveries.

Particularly scientific knowledge in a region refers to local research activities that relate to formal models and codifications (Asheim et al. 2011). Examples are scientific researchers in fields bioinformatics, genetics and nanotechnology. Inventors often acquire this type of knowledge through university's scientific open sources and/or collaborations with scientists. In this paper, we define the regional expertise in a specific scientific field in comparison with other science's domains in the focal region as well as with the focal science at the national level.

The scientific expertise in a region may promote local inventors to identify and refer scientific knowledge faster. Due to the local scientists' expertise in a specific field and the proximity of local inventors to these knowledge sources from research centers and universities, these conditions help local inventors to update the rapid changing about novel knowledge (Barney 1991; Wernerfelt 1984), have a menu of options to consider (Bikard and Marx 2018) and refer the most valuable and relevant scientific knowledge for their innovation creation (Ahuja and Katila 2004; Cassiman et al. 2018; Fleming and Sorenson 2004; Meyer 2000). The diffusion of scientific information can take place through research collaborations and mobility between researchers in public sectors and R&D staff in private sectors (Breschi and Lissoni 2009).

Nevertheless, the fundamental condition for local inventors to identify and refer scientific publications faster is dependent on whether a particular science is relevant to the focal technological innovation. Otherwise, local science does not promote the rapid diffusion of knowledge. For example: if scientists in a region have relatively scientific expertise in biomedical research and chemistry and local inventors working in transportation and furniture technologies, there is not identically relevant between that local science and technology. That scientific expertise could not help to local inventors in term of searching and identifying the relevant scientific knowledge in transportation and furniture science. Hence, the diffusion of knowledge across two streams could not happen.

However, if local inventors working in pharmaceuticals and organic fine chemistry technologies, which are relatively relevant to the current scientific expertise in biomedical and chemistry sciences, they may acknowledge the correspondent science faster. Indeed, Audretsch and Feldman (1996) show that specific scientific knowledge sources locally diffuse to certain industries that have a certain degree of relatedness. The scientists in these fields may not only diffuse their research ideas, publications in their social's networks but also bridge inventors to their scientific community, which can reside inside and outside their region. As a result, the scientific expertise of the region affects the visibility and the adoptability of local inventors to scientific knowledge sources.

In sum, this hypothesis argues that the rapid diffusion of knowledge, brought through publication-patent citation, results from the scientific expertise in the region that are correspondent with the focal technological innovation of that region. Then, local inventors can take advantage of those relevant sciences and refer to other scientific knowledge sources faster.

Hypothesis 1: The scientific expertise that is relevant to the focal technology of patents reduces the time lag on published years between the cited publication and the citing patent.

### *Scientific expertise and the rate of the diffusion of knowledge across technologies*

If the underlying mechanism for the diffusion of knowledge across scientific publication and technological innovation works as our hypothesis, we may expect the underlying mechanism is held for the diffusion of technologies. In case of direct linkage between cited publications and technology innovations, which is generally claimed, the relevant science facilitates inventors to refine, select and combine different knowledge elements for new combined knowledge, thus increase the value of their innovations (Ahuja and Katila 2004; Fleming and Sorenson 2004; March 1991).

In case of indirect linkage between cited publications, the relevant science may indicate whether the pursuing technologies of patent keeps in space with scientific knowledge (Meyer, 2000; van Vianen et al., 1990). When the process of innovation and scientific discovery simultaneously occurs, inventors can believe that the new knowledge about scientific and technological fields will lead to valuable innovations (Stephan 1996) or to involve in a promising field for future expansion or growth (van Vianen et al. 1990).

In short, the local scientific expertise provides local inventors with a means to realize, acquire potential scientific knowledge or to verify the value of their innovations.

Hypothesis 2: The scientific expertise that is relevant to the focal technology of patents increases the number of citations it receives from future patents.

## **Data and research methods**

### Data and sample selection

The theory presented in previous sections suggests several relations between the scientific expertise accumulated in a region and the capacity of local inventors to exploit faster

and better useful and relevant scientific knowledge. The key dependent and independent variables rely on 743,693 French patents granted by the European Patent Office from 1990 to 2015, retrieved from the PATSTAT database (version fall 2015). Each patent provides information about the application year, the priority year, the publication year, the inventors of the patent, and citations to patents previously granted or to non-patent prior-art references (NPRs). To test our hypotheses, we built a longitudinal dataset combining patents technological characteristics and related references to scientific work. Technological characteristics of patents are based on the International Patent Classification (IPC) which assigns each patent to one or several pre-define technological classes<sup>13</sup>. We use the last version of the IPC<sup>14</sup> consisting of 35 technological classes (Schmoch 2008).

Then, we created a subsample of science based patents. Following prior literature, we used non-patent references (NPRs) cited in patent data. Then, we created dyads between each patent and the NPRs cited on the front page of the patent (Ahmadpoor and Jones 2017; Cassiman et al. 2008; Fleming 2001; Fleming and Sorenson 2004; Meyer 2000 Narin and Breitzman 1995). Among the 743,693 patents collected, we found 100,377 patents citing 275,951 NPRs.

Admittedly, NPRs citations are imperfect measures of knowledge flow. NPRs are prior-art citations of various sources, such as books, Internet, or patent granted by the Japanese office that are not necessary related to scientific work. A simple count of NPRs may be an ambiguous

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<sup>13</sup> There are other classification systems available such as the US Patent Classification (USPC), the Cooperative Patent Classification (CPC). They differ in the level of granularity and pre-define association to patent applications. Concordance tables are available but imperfect. They all have interests and disadvantages. Comparing IPC and USPC, Harris, Arens, and Srinivasan (2010) show that USPC has a far tighter focus (163,000 entries compared to 71,000 for the IPC) and provides better information on the invention's true purpose by being more precise about technologies used in patents. However, as a result of greater granularity, USPC proves much less effective in covering a large variety of patents. Therefore, we selected the IPC system to be able to include more diverse patents in the analysis.

<sup>14</sup> IPC has been updated through a collaborative work between the German Fraunhofer ISI, the French Observatoire des Sciences et des Technologies (OST) and the French patent office (INPI).

and imprecise measure of the use of scientific references (Cassiman et al. 2008). To overcome the risk of constructing a noisy dataset, we only selected references of articles published in scientific journals. This is a very conservative strategy since it excludes several scientific sources such as books and conference proceedings. Identifying scientific publications in the list of NPRs is challenging because each information (such as title, journal name, volume and issue number, authors' name, year of publication, etc.) are sometimes missing or, when included, truncated or misspelled. Furthermore, scientific references are recorded as unstructured information often grouped in the same cell, and not necessarily in a systematic order, thus increasing the computational challenge. To exploit such unstructured data, we developed an algorithm using Google scholar search engine to identify and extract the title of the article, the academic journal where the article has been published, the year of publication, and the geographic location of the authors. We obtained 26,068 patents citing 61,486 scientific articles (thus 61,486 patent-paper dyads) published in 15,012 academic journals.

NPRs also can overemphasize science-to-patent links when both patents and scientific articles result from the same research project (Meyer, 2000). This may be a concern since it may inflate the role of regional scientific expertise in explaining time since scientists collaborating in research projects often are collocated members of the same university, institution or corporation. Then the expertise of the employer, more than the regional expertise, would explain lower time lag. We address this concern testing our relations with a sample excluding observations where the patent and the paper of a dyad is owned by the same institution. For a more conservative test we also excluded all patent-paper dyads if the paper and the patent were published the same year.

However, despite these limitations, recent studies relying on interviews (Bikard and Marx 2018; Sampat and Lemley 2011), questionnaire survey (Wesley M Cohen et al. 2002), or

comparative statistics between NPRs and machine learning algorithms (Callaert et al. 2011) converged to demonstrate that NPRs provide accurate measures of inventors' awareness of scientific contributions and prove better proxies of knowledge flows than patent-to-patent citations (Matt and Aaron 2019).

### *Method and Measurement:*

#### *Dependent variables*

##### *Patent-to-paper time lag*

For each patent-paper dyad, the diffusion of knowledge across science and technology in a region, *Patent-to-paper time lag*, is measured using the difference between the year of publication of the scientific article and the priority year of the citing patent written by a local inventor. Recent literature estimating time difference between scientific publications and citing patents (Finardi 2011; Fukuzawa and Ida 2016; Popp 2017) has generally considered the application year of the citing patent in their measure. Following Heinisch et al., (2016), we rely on the priority year to get more accurate information on the earliest date when the original invention has been disclosed. Priority date refers to the earliest filing date of the first application in a patent family, that is all patent applications filed in any patent office covering similar technical content and having similar priority claims. It therefore is the most accurate date to report an invention (Maraut et al. 2008). The mean *Patent-to-paper time lag* is 3,83 years ranging from -24 years to 120 years. Negative values (4,509 observations, i.e. less than 0.06% of the patent-paper dyads) may be due to reporting errors, or to scientific papers published earlier than the application year but later than priority year. Under the evaluation process of applications, examiners may decide to include a prior-art reference in order to facilitate the understanding of the underlying technology that is claimed to be protected. Thus, this reference

may have been published earlier than the application date, but later than the priority date (Akers 2000). We dropped observation with a time lag lower than 5 years and replaced all other negative observations by zero-time lag. In addition, the distribution is skewed with a long right tail. These outliers represent well-known and widely diffused articles. For estimation, we drop observations with a time lag of greater than 25 years before the patent application. This eliminated 1.5% of the patent-paper dyads. Thus, we capture 98.5% of the observations.

In the next step, we allocated each patent (from the patent-paper dyads) to one or several French regions (NUTS3 level) based on the post mail address of the inventors (Leten et al. 2014; Ter Wal 2013). Determining the geographic location of inventors is not easy because the great majority of inventors reports incomplete, or misspelled addresses, or do not report address at all. Following the OECD approach to create the REGPAT database (Maraut et al. 2008), we allocated each patents to one or several regions (NUTS3) based on a search of the postcode of the inventors. When the postcode was missing, we used the town name to run a second search if mentioned. When the identified town name was not unique, we did a complementary manual check to see if we could identify the inventors' location thanks to the location of his employer or the presence of the owner in the considered region. In case no town was mentioned, no NUTS3 code was allocated. However, unlike REGPAT, we did not substitute the owner address when the inventor's one was missing. The owner generally is a corporation or a university who reports the headquarters' address, which may not be in the region. Finally, a patent may have different authors located in different regions. Considering knowledge as a non-rival good, we assigned the patent to every region where one of the inventors is located. Of the 26,046 science-based patents, 10,177 (38%) patents have information about the geographic location of at least one inventor. The average, region produces 11,55 patents citing 293,74 scientific papers per year, ranging from a minimum of 1 to a maximum of 258 patents per year and 1 to 1359 scientific citations.

The two additional dependent variables, impact and influence, are designed to measure the impact of each patent in both direct count and indirect citing patent trees (Hall, Jaffe, and Trajtenberg 2001; Trajtenberg 1990). Inventors and examiners who are entitled to cite prior work generally cite prior patents that are directly linked to the citing patent (Corredoira & Banerjee, 2015). Thus, following Corredoira et al. (2018), we define the variable *Impact* as the measure of the usefulness of the focal patent on future inventions. Our variable influence intends to capture indirect impacts of the focal patent to subsequent generations of forward citations (Corredoira & Banerjee, 2015; Corredoira et al., 2018). This is particularly important to identify breakthrough inventions that have a high and broad long-term influence but do not necessarily have a high (first generation) impact (Corredoira et al. 2018). Finally, we dropped patents whose priority year was earlier than 1994. As we will explain further in the independent variable section, this is because we build our regional scientific expertise on a 5-year aggregation moving window.

### *The Impact*

*The Impact* is the total number forward citations received by a patent. Most citations are received within ten years after receipt of the patent (Hall et al. 2001). Thus, we calculated *The Impact* of patent (i) as the number of citations received within the ten years from the patent grant date.

$$Impact_i = vA_i \quad (1)$$

Where  $v$  is a vector of ones, capturing the significance of each patent and  $A_i$  is the number of patents that cite the focal patent (i).

Notice that granted patents whose priority date is later than 2005 may see their forward citations number be significantly truncated. This should have a minor effect on our result since

we include year-fixed effects. Furthermore, we did a robustness check with a dataset of patents with priority year from 1994 to 2004.

### *The Influence*

This variable considers all direct and indirect forward citations filed within ten years after the focal patent was granted. Following Corredoira et al. (2018), *The Influence* is calculated as

$$Influence = \sum_{k=0}^n A^{Tk} \quad (2)$$

where  $k$  is the citation generation,  $A^T$  is the transpose of the adjacency matrix by patent citation.<sup>15</sup>

### *Independent variables*

#### *Regional scientific expertise*

In this article, we are interested in estimating the effect of regional expertise on local inventors' capacity to better exploit available scientific knowledge. To measure regional scientific expertise in each specific domain we collected all scientific articles published by French authors<sup>16</sup> and assigned them to a pre-defined scientific domain. More precisely, we extracted 1,481,784 scientific articles published by a French author between 1990 to 2015 from Thomson Reuters' Web of Science (WoS). Then, relying on the academic journal where it has been published, each paper was then assigned to one of the 22 scientific domain as provided by

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<sup>15</sup> In the original model (Corrodeira and Banarjee, 2015) weighted patents based on their relative contribution, such as claims for instance. We follow Correira, Goldfarb, and Shi (2018) and assume a contribution of one for every patent, thus giving equal weight to all generations.

<sup>16</sup> Authors affiliated to a French university, public or private research institution or corporation.

the Science-Metrix journal classification (Archambault et al. 2011)<sup>17</sup>. Several journal classifications are available and used by the literature or by research assessment bodies. Science-Metrix classification (SMc) used several established classification systems to create a unique taxonomical tree<sup>18</sup>. The advantage of SMc is its extensive coverage of academic journals including journals reported in Scopus and Web of Science (WoS) lists. Science-Metrix classification assigns each individual journals to single, and mutually exclusive categories. Although publications and authors' activity increasingly rely on interdisciplinary work and may be assigned to several scientific fields or subfields (Glänzel and Schubert 2003), the allocation to several fields or subfields may create ambiguous information and prevent consistent comparison exercises (Gómez et al. 1996b). Then, using the post code of the address of the author's affiliation, each paper was allocated to a French region. Similar to the geographic allocation of patents, co-authored papers may have been allocated to several regions if co-authors work in different regions. Depending on scientific domains, scientific publication can take several years. Thus small regions may have erratic records of publications providing unreliable information of local scientific expertise. To smoothen the RSE variable trend, we sum patent over the past five years to calculate the regional yearly publication records per domain. Then, the number of publications in domain (j) in year t in a region is:

$$\overline{P_{jt}} = \sum_{t=0}^{t=4} P_{j,t-1} \quad (3) \quad \text{where } t = \{1994, \dots, t, \dots, 2013\}$$

Finally, we used the well-known relative –or revealed- comparative advantage that have been used to measure technological expertise (Archibugi and Pianta 1994; Malerba and

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<sup>17</sup> More details in their paper.

<sup>18</sup> To associate journals and with research fields and subfields, Science –Metrix used the new US NSF classification, -based on the Computer Horizons Inc. classification (CHI), initially designed by Mark Carpenter and Francis Narin in the 1970s-, the WoS classification managed by Thomson Reuters, the Evaluation of Research Excellence (ERA) classification designed by the Australian Research Council, the revised Field of Science and Technology (FOS) Classification in the Frascati Manual, and the European Research Council (ERC) classification. The list is freely accessible under a creative commons science ([www.science-metrix.com](http://www.science-metrix.com))

Montobbio 2003), or national product specialization in international trade (Dalum 1999; Hausmann and Hidalgo 2011; Hidalgo et al. 2007; Laursen and Salter 2004). This variable indicates for every region the relative share of scientific publications in a specific domain compared to the share of publications in this domain at national level. More precisely, the scientific expertise of region  $r$  is measured as follows

$$RSE_{jr} = \frac{\sum P_{jr} / \sum P_r}{\sum P_{jN} / \sum P_N} \quad (4)$$

where  $P_{jr}$  is the total number of scientific publications in domain ( $j$ ) in region ( $r$ );  $P_r$  is the total number of scientific publications in region ( $r$ );  $P_{jN}$  is total number of French publications in domain ( $j$ ); and  $P_N$  is the total number of publications in France. Then, we have 22 RSE per region per year ranging from 0 to 1155 and a mean value of 1,15. An RSE above 1 in a scientific domain suggests a relative expertise higher than the average expertise in the country. Finally, we normalized RSE to be bounded between 0 and 1 as follows:

$$RSE'_{jr} = \frac{RSE_{jr} - \text{Min}RSE_j}{\text{Max}RSE_j - \text{Min}RSE_j} \quad (5)$$

One limitation of this measure is that expertise actually relies on the level of specialization in a specific domain in a region. It follows that very small and specialized regions are more likely than large and diversified regions to have a high RSE in one domain. We address this problem in the model specification section by weighting our estimations by taking into account the depth of the scientific expertise used in the patent of the focal patent-paper dyad.

### ***Control variables***

#### *Science and technology links*

It is likely that scientific expertise in a specific domain will be more useful to inventors exploiting technologies that can benefit from this domain. For instance, expertise in biology is more likely to be used by inventors working on biotechnology-based patents than inventors working on mechanical engineering-based patents. Thus, we included a control variable for *Science-technology links*. The construct the variable we applied the survivor principle to estimate the level of applicability of a scientific domain in all technological fields. The survivor principle implies that more efficient exploitations of a scientific domain by a specialist of a technological filed is more likely to be reused (Lien and Klein 2013; Nesta and Saviotti 2005; Teece et al. 1994). Thus, over time, the intensity of citations of a scientific domain in patents will depend on its “revealed” usefulness.

We use a parametric based measure to estimate the intensity of the links between a scientific domain and a technological field. Let  $J_{ij}$  be the number of patents assigned to a technological field  $i$  and citing a scientific domain  $j$ . Then, considering  $J_{ij}$  as a hypergeometric random variable, the probability of drawing  $J$  patents associated with both technology  $i$  and scientific domain  $j$  follows the hypergeometric density function (Population  $N$ , special members  $J_i$ , and sample size  $J_j$ )

$$P(X_{ij} = x) = \frac{\binom{J_i}{x} \binom{N - J_i}{J_j - x}}{\binom{N}{J_j}} \quad (6)$$

where is  $X_{ij}$  is the number of patents assigned to both  $i$  and  $j$ , and  $x$  is the hypergeometric random variable. Its means value (expected frequency) and variance are:

$$\hat{J}_{ij} = \mu_{ij} = E(X_{ij} = x) = \frac{J_i J_j}{N} \quad (7)$$

It follows that the intensity of links, that is the level of applicability, between scientific domain  $j$  and technology  $i$  is determined by the difference between the expected value  $\mu_{ij}$  of random co-occurrence between technology  $i$  and scientific domain  $j$  and the actual number  $J_{ij}$  of co-occurrences observed  $i$  and  $j$ . Hence, the measure of applicability of the scientific domain  $j$  to inventions based on technology  $i$  is captured by the  $\lambda_{ij}$ , where

$$\lambda_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}, \quad \lambda_{ij} \in R \quad (8)$$

### *Search proximity*

The influence of a paper may be dependent on the proximity of an invention to existing and well-established technologies. Searching in the neighborhood of well-known solutions or using familiar technologies increases the likelihood of a patent to be cited (Fleming 2001). We calculated *Search proximity* by aggregating the number of references to prior patents in the focal patent (Podolny and Stuart 1995).

### *Technological novelty*

Relying on science helps developing frontier technology and therefore have higher influence of future patents (Sorenson and Fleming 2004). Therefore, the likelihood to use science may be higher when relying on cutting-edge technology, that is close to the frontier (Fleming and Sorenson 2004; Katila 2002). We included a control variable for *Technological novelty* calculated as the total number of scientific references in the patent.

### *Technological opportunity*

We included technological field dummy in our regressions to control for *Technological opportunity*. Technologies provide different opportunities to invent (Henderson and Cockburn 1994) and therefore the technology used by inventors affect the likelihood of patenting.

*Depth of scientific expertise*

One limitation of using the relative comparative advantage to measure Regional scientific expertise is the risk of inflating the level of small regions' expertise. Very small regions specialized in a given scientific domain are more likely than large and diversified regions to have a high RSE in that domain. To account for this potential bias, we control for the *depth of scientific expertise of the region*. We calculated *depth of scientific expertise of the region* (DSE) as the total number of scientific publication in the scientific domain of the focal patent-paper dyad. We normalized this variable to be bounded between 0 and 1 as follows:

$$DSE'_{jr} = \frac{DSE_{jr} - \text{Min}DSE_j}{\text{Max}DSE_j - \text{Min}DSE_j} \quad (9)$$

*Econometric models*

In both hypotheses, the dependent variables only take non-negative integer values. The Poisson regression is generally applied to the model count data (Hausman, Hall, and Griliches 1984). In order to check whether the Poisson estimator is the right choice, we do a goodness-of-fit test of the Poisson estimation in both models. Both of the deviance and the Pearson statistics are significant ( $p < 0.01$ )<sup>19</sup>. Hence, the Poisson regressions are inappropriate. Additionally, table 1 displays the descriptive variables of the two models. The time lag is highly skewed and over-dispersed across the distribution, which the variance is nearly nine times larger than the mean. The variance of the *impact* and the *influence* are much larger than their means.

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<sup>19</sup> The results can be provided as a further request.

Therefore, we use fixed effect negative binomial regressions rather than Poisson regressions.

The dependent variable  $y_r$  follows a negative binomial distribution with parameters  $\lambda_r$

$$P(Y = y_r) = \exp(-\lambda_r) \cdot \frac{\lambda_r^{y_r}}{y_r!} \quad (10)$$

The expected value for region  $r$  equals  $\lambda_{i,t}$ :

$$E(Y_r) = \beta_0 + \beta_1 RSE_r + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \quad (11)$$

where  $Y_r$  are the dependent variables,  $RSE_r$ , is the scientific expertise of region  $r$  in the scientific domain of the patent-paper dyad and  $X_i$  represent the set of control variables. are weighted by the RSE variable All our estimations used fixed-effect negative binomial regression and are robust to heteroscedasticity. *Regional specialization expertise* is may be sensitive to the size of the region. Small regions tend to have less diverse scientific knowledge portfolio, then generating the risk of inflating the level of their relative comparative advantage in the scientific domains they are specialized. To address this potential bias, all models are weighted by the *depth of scientific expertise of the region* variable. Table 1 shows descriptive statistics and table 2 shows the correlation matrix.

	Count	Mean	S.D	Variance	Min	Max
<i>Patent-to-paper time lag</i>	75500	2.38	4.61	21.25	0.00	25.00
<i>The impact</i>	75500	6.87	14.09	198.65	0.00	399.00
<i>The influence</i>	75500	1222.74	7267.69	5.28E+07	0.00	4.10E+05
<i>Scientific expertise</i>	75500	0.28	0.19	0.04	0.00	1.00
<i>Science-technology links</i>	75500	49.90	47.50	2256.31	-35.28	366.03
<i>Technological novelty</i>	75500	18.64	21.51	462.55	1.00	84.00
<i>Search proximity</i>	75500	7.48	16.26	246.36	0.00	124.00
<i>Depth of scientific expertise</i>	75500	0.25	0.29	0.09	0.00	1.00

Table 2. 1: Descriptive data

	1	2	3	4	5	6	7	8
<i>Patent-to-paper time lag</i>	1.000							
<i>The impact</i>	0.110	1.000						
<i>The influence</i>	0.029	0.447	1.000					
<i>Scientific expertise</i>	0.008	-0.050	-0.073	1.000				
<i>Science-technology links</i>	-0.033	-0.092	-0.045	0.230	1.000			
<i>Technological novelty</i>	0.011	0.053	-0.040	0.150	0.153	1.000		
<i>Search proximity</i>	0.012	0.114	0.055	0.018	0.003	0.324	1.000	
<i>Depth of scientific expertise</i>	-0.042	-0.111	-0.056	0.195	-0.040	-0.079	-0.069	1.000

Table 2. 2: Correlation matrix

### ***Clustering technological groups of industries***

A few of recent studies have investigated the time lag by using publication-patent citations. Their findings are heterogenous in the time lag across industries. More specifically, in the life and medical sciences fields in Japan, the time lag for paper-patent citations is six years since its publications (Fukuzawa and Ida 2016). It takes about 15 years for the peak citations in biofuels, solar and wind energy technologies (Popp 2017). Similarly, the time lag in nanotechnology is around 3-4 years (Finardi 2011). Therefore, we test the underlying mechanism in the full dataset of the sample as well as the separate industries.

We cluster patents in each region according to its technology, which bases on the WIPO technological classification. This classification builds from the codes of the International Patent Classification (IPC). While the IPC generally bases on sector classification, which is defined by typical products and describes the main activities of enterprises, the WIPO relies on technologies used in the production processes. Because patents are oriented towards the legal protection of technologies being used in an invention, the usage of the WIPO classification to classify patent's technologies is an appropriate way to compare technological activities across

regions, where innovation activities occur. Accordingly, there are five fundamental industrial groups based on technological fields: electrical engineering, instruments, chemistry, mechanical engineering and other fields. Under each technological field, there are several industries. For example, chemistry technology group comprises of two small groups of technology.

The first set of technologies are organic fine chemistry, biotechnology, pharmaceuticals, polymers, food chemistry. The second set of technologies in basic materials chemistry, materials and metallurgy, surface technology and coating, micro-structure and nano-technology, chemical engineering and environmental technology. However, one can see that the first set of technologies directly involves the product components for the final goods such as medicine and food. Meanwhile, the second set of technologies involves the materials and machines used in the production processes of the first group. Additionally, the instruments group includes technologies in optics, measurement, analysis of biological materials, control, and medical technology, which are also intermediate technologies used in other industrial technologies (e.g. food, pharmaceutical). Therefore, we merge the second group of chemistry into the group of instrument technologies. Besides, the group of other technology fields include furniture, games, other consumer goods and civil engineering, which mainly use mechanical engineering technologies to their production process. We further merge this group into mechanical engineering. Other technology groups are kept the same as the WIPO classification<sup>20</sup>. Finally, our econometric models will be estimated based on four different

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<sup>20</sup> [https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo\\_ipc\\_technology.pdf](https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf) for more discussion. Source: WIPO IPC- Technology Concordance Table.

technological industry groups: electrical engineering, instruments (or intermediate technologies), chemistry and mechanical engineering.

Due to the limited observations of technology groups (electrical engineering and mechanical engineering), there is about 9.8% of the full sample. It means the total observations of instruments and chemistry groups have 92% of the full sample. Therefore, we will run the regression for the full sample as well as the separate technology groups of instruments and chemistry.

## **Results**

Table 3 displays the results of the first hypothesis, which examines the impacts of regional scientific expertise on the time lag. Model 1 and 2 are estimated under the full sample. Model 3-6 are limited the sample to the different technology's groups. In general, the result shows that scientific expertise has a significantly negative correlation to the time lag, which supports the first hypothesis. However, this relationship is not monotonic. The model 2 shows that scientific expertise has an U relationship with the time lag. The result implies that local science expertise facilitates local inventors to identify or to verify the relevant scientific publication faster. However, at a certain threshold of scientific expertise, the local science increases the time for searching new knowledge. Calculating the point of inflection on the curves will show the threshold of scientific expertise that can help local inventors to identify and/or verify the relevant scientific publications.

Besides, the effects vary across the technological industry groups. Particularly, the local science expertise reduces the time lag of publication-patent citation in the instruments and chemistry industry group (model 4 and 5), while the negative relationship is not significant in the mechanical engineering industry group (model 6).

VARIABLES	Negative binomial regression estimation with iweight and vce options					
	Model 1 Only control variables	Model 2 All sample	Model 3 Electrical engineering	Model 4 Instruments	Model 5 Chemistry	Model 6 Mechanical engineering
<i>Dependent variable: Patent-to-paper time lag</i>						
<i>Scientific expertise</i>		-1.848*** (0.344)	0.806 (1.699)	-2.907*** (0.787)	-1.151*** (0.401)	-4.014 (3.447)
<i>Scientific expertise (sq)</i>		2.959*** (0.453)	-4.43 (2.719)	4.336*** (1.082)	2.112*** (0.516)	3.777 (5.007)
<i>Science-technology links</i>	0.000 (0.001)	0.000 (0.001)	-0.003 (0.004)	-0.003** (0.001)	0.000 (0.001)	0.001 (0.014)
<i>Technological novelty</i>	0.000 (0.001)	-0.001 (0.001)	-0.034 (0.024)	0.001 (0.002)	0.000 (0.001)	0.081*** (0.024)
<i>Search proximity</i>	-0.001 (0.001)	-0.001 (0.001)	-0.004 (0.006)	0.000 (0.005)	-0.001 (0.002)	-0.023*** (0.007)
<i>Region-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Science-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Technology-fixed effects</i>	Yes	Yes	-	-	-	-
Constant	0.422*** (0.111)	0.507*** (0.115)	0.212 (0.337)	1.182*** (0.192)	0.522*** (0.120)	2.161*** (0.668)
Observations	73703	73703	5983	20418	46050	1252
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table 2. 3: Regression analysis of the characteristics of regional scientific expertise on the time lag

Furthermore, we did a robustness check with a dataset of patents with priority year from 1994 to 2004. Table 4 shows the results under the negative binomial estimations. In general, our first hypothesis is still consistent. Furthermore, the coefficients turn to be significant in the mechanical engineering industry group (model 12).

VARIABLES	Negative binomial regression estimation with iweight and vce options					
	Model 7 Only control variables	Model 8 All sample	Model 9 Electrical engineering	Model 10 Instruments	Model 11 Chemistry	Model 12 Mechanical engineering
<i>Dependent variable: Patent-to-paper time lag</i>						
<i>Scientific expertise</i>		-2.225*** (0.345)	-0.892 (1.906)	-2.580*** (0.727)	-1.995*** (0.412)	-8.061** (3.719)
<i>Scientific expertise (sq)</i>		3.320*** (0.449)	-0.200 (3.150)	3.847*** (0.966)	2.974*** (0.533)	11.694** (5.261)
<i>Science-technology links</i>	-0.000 (0.001)	-0.000 (0.001)	0.001 (0.004)	-0.003 (0.002)	-0.000 (0.001)	0.016 (0.023)
<i>Technological novelty</i>	0.003*** (0.001)	0.004*** (0.001)	0.030* (0.016)	0.005** (0.002)	0.004*** (0.001)	0.096*** (0.024)
<i>Search proximity</i>	-0.003 (0.002)	-0.003** (0.002)	-0.005 (0.006)	-0.001 (0.005)	-0.003* (0.002)	-0.025*** (0.006)
<i>Region-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Year-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Science-fixed effects</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Technology-fixed effects</i>	Yes	Yes	-	-	-	-
Constant	0.814*** (0.124)	0.739*** (0.119)	0.367 (0.365)	1.058*** (0.207)	0.278** (0.119)	2.328*** (0.674)
Observations	58,101	58,101	4,402	15,156	37,604	939
Robust standard errors in parentheses						
*** p<0.01, ** p<0.05, * p<0.1						

Table 2. 4: Robustness checks for the sample between 1994-2004

We are going to check whether the locally scientific expertise affects the influence of the focal patents in table 5, which indicates the diffusion of knowledge across technological innovations. Models 13-16 estimate the underlying mechanism that affect the *impact* of patents and models 15-20 examine the *influence* of patents.

VARIABLES	The impact				The influence			
	Model 13 Electrical engineering	Model 14 Instruments	Model 15 Chemistry	Model 16 Mechanical engineering	Model 17 Electrical engineering	Model 18 Instruments	Model 19 Chemistry	Model 20 Mechanical engineering
<i>Dependent variable: the total number forward citations received by a patent</i>								
<i>Scientific expertise</i>	0.300 (0.719)	0.689** (0.350)	0.425 (0.363)	-1.130 (1.325)	1.560 (1.430)	1.467** (0.653)	1.405** (0.695)	-11.581*** (2.321)
<i>Scientific expertise (sq)</i>	-1.741 (1.240)	-2.047*** (0.493)	-1.080** (0.482)	0.582 (2.249)	-3.276 (2.587)	-4.270*** (0.856)	-2.443*** (0.814)	11.386*** (3.069)
<i>Science-technology links</i>	0.005** (0.002)	0.001 (0.001)	-0.001*** (0.000)	0.003 (0.007)	0.028*** (0.004)	0.008*** (0.001)	-0.002** (0.001)	0.026*** (0.010)
<i>Technological novelty</i>	0.023*** (0.006)	-0.001 (0.001)	-0.001** (0.001)	0.055*** (0.015)	-0.008 (0.011)	-0.022*** (0.003)	-0.017*** (0.001)	0.110*** (0.025)
<i>Search proximity</i>	0.045*** (0.005)	0.022*** (0.002)	0.008*** (0.001)	0.010*** (0.002)	0.061*** (0.008)	0.027*** (0.005)	0.008*** (0.002)	0.005 (0.004)
<i>Region-fixed effects</i>	0.016 (0.420)	-0.711*** (0.116)	-0.141* (0.083)	-1.012* (0.545)	0.109 (0.527)	-1.146*** (0.142)	0.120 (0.141)	-1.539*** (0.556)
<i>Year-fixed effects</i>	-0.121 (0.163)	-0.185*** (0.056)	0.022 (0.060)	-0.048 (0.274)	-0.127 (0.294)	-0.134 (0.123)	0.157 (0.125)	0.763 (0.469)
<i>Science-fixed effects</i>	0.111 (0.098)	-0.023 (0.044)	0.047 (0.059)	-0.177 (0.135)	0.222 (0.192)	-0.192** (0.097)	0.036 (0.136)	-0.197 (0.256)
<i>Constant</i>	1.413*** (0.166)	1.072*** (0.106)	1.340*** (0.080)	1.226*** (0.292)	6.864*** (0.330)	5.966*** (0.210)	5.595*** (0.161)	7.248*** (0.612)
Observations	5,872	20,051	45,601	1,229	5,872	20,051	45,601	1,229

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 2. 5: Regression analysis of the characteristics of regional scientific expertise on the forward patent citation counts

At first, the *search proximity*, which is the total number of cited patents in the focal patent, has a positive coefficient with the impact and the influence of the patent. The coefficients are consistent to all industrial technology groups. However, the sign of coefficients between science-technology links and technological novelty are different accorss technology groups. Generally, *the impact* and *the influence* of a patent have U-inverted relationships with the *scientific expertise*.

The relationship between the *scientific expertise* and the value of the focal patent is U-shape (model 20). However, this result does not rule out our second hypothesis because the number of observations in this group is only 1.6% of the total observation. Otherwise, one may

argue that local scientific expertise only facilitate the value of the focal patent if it reaches a certain threshold. The overall result confirms our hypothesis that scientific expertise stimulates the diffusion of knowledge across technological innovations.

Then we tested our second hypothesis for a sample between 1994-2004 (table 6). The results are consistent to those in the table 5.

**Table 6: Regression analysis of the characteristics of regional scientific expertise on the forward patent citation counts**  
**Robustness checks for the sample between 1994-2004**

VARIABLES	The impact				The influence			
	Model 21 Electrical engineering	Model 22 Instruments	Model 23 Chemistry	Model 24 Mechanical engineering	Model 25 Electrical engineering	Model 26 Instruments	Model 27 Chemistry	Model 28 Mechanical engineering
<i>Dependent variable: the total number forward citations received by a patent</i>								
<i>Scientific expertise</i>	-0.559 (0.807)	1.207*** (0.389)	0.019 (0.398)	0.957 (1.509)	3.782*** (1.457)	3.418*** (0.791)	1.444** (0.680)	-11.444*** (3.092)
<i>Scientific expertise (sq)</i>	0.710 (1.389)	-2.628*** (0.533)	-0.592 (0.536)	-4.187 (2.546)	-7.458*** (2.318)	-6.277*** (1.007)	-2.044** (0.842)	8.972* (4.725)
<i>Science-technology links</i>	0.005* (0.003)	0.001* (0.001)	-0.001*** (0.000)	0.004 (0.011)	0.027*** (0.005)	0.009*** (0.002)	-0.003*** (0.001)	0.022 (0.018)
<i>Technological novelty</i>	0.047*** (0.008)	-0.003** (0.001)	-0.003*** (0.001)	0.051*** (0.015)	0.029*** (0.011)	-0.027*** (0.003)	-0.017*** (0.001)	0.105*** (0.027)
<i>Search proximity</i>	0.040*** (0.005)	0.024*** (0.002)	0.009*** (0.001)	0.007*** (0.002)	0.062*** (0.008)	0.032*** (0.004)	0.009*** (0.002)	0.001 (0.004)
<i>Region-fixed effects</i>	0.309 (0.301)	-0.574*** (0.133)	-0.139 (0.089)	-0.352 (0.429)	-0.297 (0.502)	-0.796*** (0.156)	0.114 (0.150)	-0.763 (0.478)
<i>Year-fixed effects</i>	0.128 (0.178)	-0.109* (0.061)	0.050 (0.068)	0.138 (0.344)	-0.011 (0.312)	0.033 (0.151)	0.097 (0.121)	1.308* (0.671)
<i>Science-fixed effects</i>	0.164 (0.122)	0.084 (0.053)	0.100 (0.068)	0.061 (0.166)	0.134 (0.252)	-0.014 (0.136)	0.009 (0.135)	0.116 (0.312)
<i>Constant</i>	1.401*** (0.178)	0.843*** (0.107)	1.319*** (0.084)	0.937** (0.387)	6.686*** (0.334)	5.492*** (0.228)	5.304*** (0.173)	7.087*** (0.770)
Observations	4,301	14,862	37,184	919	4,301	14,862	37,184	919

Robust standard errors in parentheses

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 2. 6: Regression analysis of the characteristics of regional scientific expertise on the forward patent citation counts. Robustness checks for the sample between 1994-2004

The results support our idea that the locally scientific expertise, which is correspondent with the focal technology, facilitates local inventors to search and/or verify the scientific

publications faster. The process helps gain and confirm whether the current technology of the focal innovation is in space with the scientific discoveries. Second, the findings also reveal that scientific expertise is also a mechanism of the diffusion of knowledge across technological innovations. However, the impacts are different from various technology groups. In total, these results provide strong evidence about the role of scientific expertise on the diffusion of knowledge across science and technology as well as technologies.

## **Discussion and conclusion**

Scholars have investigated different mechanisms for the diffusion of knowledge across innovations. However, there is no study to answer “what is the mechanism for the diffusion of knowledge between a scientific publication and technological innovation”. We believe that this question is an important one, not only because science is generally assumed to be a source for innovation, but also because it helps to understand the process of referencing or of identifying the useful scientific publications. If we can understand the underlying mechanism for this process, we may be able to deliver appropriate strategies and policies at different levels: inventor-, firm-, industry-, regional-, and national levels.

This paper makes several contributions. First, it is the first paper to our knowledge that link technological fields and scientific domain at the regional level. It, therefore, can disentangle the role of the specific links and the role of geographic proximity in producing impactful innovation. Second, to our knowledge, except for Sorenson and Fleming (2004), prior literature has given little attention to understanding the underlying conditions that accelerate the process of references to scientific publications. Results show that scientific expertise in the region, which is correspondent to the focal technological innovation, leads inventors to search, identify or verify relevant scientific materials.

In addition, the underlying mechanism of scientific expertise is also applicable to the diffusions of knowledge across innovations. The basic idea is that patents reference the scientific literature, which reflects broad dissemination of public knowledge, receive more citations. The effect indicates the norm of the diffusion of knowledge (Sorenson and Fleming 2004; Sorenson and Singh 2007). Our findings support this idea in a sense that scientific expertise may facilitate the search process of inventors to identify the most relevant science. One may reasonably ask how much of the value of the effect, and we can say it is significant.

Third, knowing inventor-given references sets us apart from the prior studies that primarily focus on analysing the scientific publications given by patent examiners but not on the references of patent inventors (van Vianen et al. 1990). The data also leads us to consider the heterogeneity problems of specific fixed-effects that may affect the difference of the time lag between publication and patent, such as regional and year fixed effects. Additionally, the observed sample of all French regions over a long period helps us to overcome heterogeneity problems of inventor preferences on scientific literature (such as the language barrier) because all publication-patent citations are tested under the same national context.

Four, while the first generation of forward citations count measures the *impact* of cited patent to the directly citing patents, the multi-generational forward citation tree captures the *influence* of the focal patent to technological trajectory over the long term because this measurement counts both the direct and indirect forward citations of the focal patent (Corredoira and Banerjee 2015; Corredoira et al. 2018). This measurement allows us to observe the impact of the diffusion of knowledge on the overall technological progress. In addition, the ten-year window of forward citation count allows us to capture the heterogeneity on the time lag of publication-patent citations in different technologies. More specifically, the most common measurement of the *impact* of the patent is to count the number of prior art citations

that the patent received during the first five years since it was granted (Dibiaggio, Nasiriyar, and Nesta 2014; Fleming and Sorenson 2004). This five-year window of forward citation count is a short time, which could not measure the *impact* of the patent in some technologies. For example, Fukuzawa and Ida (2015) find that the life and medical technology group takes six-to-eight years for the peak citation of the patent. It also takes eight-to-ten years for the time lag of patent-patent citations in biofuels, solar and wind technology group (Popp 2017). As a result, our ten-year window count of forward citation is enough long-period for a patent to be recognized and cited by other patents, which may capture the differences in the diffusion of knowledge across technologies.

In practical relevant, answering these questions help different stakeholders to have better strategies and policies relating to the linkage between science, innovation and technological progress. From an R&D policy' perspective, understanding the underlying mechanism to reference scientific publications of inventors may help policymakers to guide and accelerate the scientific investment. For industry, the diffusion of knowledge of science may help industrial sectors to rejuvenate its innovation advantage by acquiring potentially scientific knowledge faster. Consequently, patents, which cite scientific publications, have better impacts on future technology. Firms and inventors may have oriented-direction of search and of combining the newly acquired knowledge.

In conclusion, we adopt the current literature about the relationship between science and technology. We try to understand under which condition inventors may refer to scientific publication. Then we predict the outcome of the search process. We argue that science should be correspondent to the focal technologies bring benefits to local inventors. Finally, our work raises several questions that relate to the context of science-technology linkage. For example, at the paper-patent citation, what is the value of the focal patent when it cites both basic and

applied scientific publication? At the regional level, does the degree of connectedness between science and technology affect the innovativeness of innovation of the region. Answers of these questions could further explain the dynamic linkage of science-technology.

## **Chapter 3**

### **Regional Alignment and Innovative Performance of Regions**

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## **Regional Alignment and Innovative Performance of Regions**

### **Abstract**

We show that regions can create critical resources providing local firms/inventors with higher innovative capacities. More precisely, we argue that regions exhibiting a combination of complementary scientific and technological expertise (we call regional alignment) will have a higher likelihood to produce useful and valuable innovation. Further, by conceptualizing innovation as a result of a combination search, we show that synergies between scientific expertise and technological specialization provide aligned regions with a higher capacity to explore into new and unfamiliar knowledge. We use a unique and detailed dataset of French patents and scientific publications (1990-2015) associated with 93 French regions. Our results provide an exciting discussion on the role of industry composition of regions on innovative performance as well as a better understanding of the role of universities in regional innovation systems.

**Keywords:** *technology; science; platform, regional alignment, innovation.*

*JEL Classification: O38, O33, D83*

## **Introduction**

Over the years, scholars in geography innovation strive for understanding how the processes of knowledge creation occur and whether the regional context influences these processes. Studies show that regions vary in terms of industrial specialization (Marshall, 1920), diversification (Jacobs 1969), industrial clusters (Porter 1990), network of inventors, scientists and firms (Breschi and Catalini 2010; Harmaakorpi and Melkas 2005). These specific conditions create the environment for creative learning, information exchanging and collaboration that facilitates local actors to innovate. As a result, regions are different in their capacity to innovate, thus leading to high within-country heterogeneity (Asheim, Boschma, & Cooke, 2011; Quatraro, 2016).

Among others, one of the main sources of this heterogeneity is the differences in inventors' access to external and complementary knowledge underlying the literature of regional knowledge bases (Asheim et al., 2011; Harmaakorpi & Melkas, 2005; Lazaric, Longhi, & Thomas, 2008). An extensive stream of research has quantified the differentiated knowledge bases and empirically tested their impacts on regional innovation performance (Asheim et al. 2011; Asheim and Hansen 2009; Blažek and Kadlec 2019; Grillitsch et al. 2017; Květoň and Kadlec 2018; Martin 2012). However, there is still lackage of theoretical and empirical study examing the process of knowledge creation of local inventors at the regional context. More specifically, the mechanism underlying how local inventors search and combine potential synergized elements of knowledge remains a black box. Therefore, researchers could not answer how the region facilitates local inventos to innovate by combing not only familiar but also unfamiliar knowledge elements.

Considering new knowledge results from the combinations of existing knowledge elements, the value and the innovativeness of new knowledge depend on the level of familiarity

of knowledge used in combinations. While the use of familiar combination increase productivity (Fleming & Sorenson, 2004), the engagement in explorative processes experiments new combinations (Ahuja & Katila, 2004; Phene, Fladmoe-Lindquist, & Marsh, 2006). However, searching beyond the boundaries of the traditional knowledge base generates obstacles for inventors such as high cost and uncertainty in evaluating new knowledge (Cohen & Levinthal, 1989; Kogut & Kulatilaka, 2001), barriers and risks on acquiring new knowledge (e.g. the lack of shared language and trust) (Kogut & Zander, 1992; Von Hippel, 1994).

Moreover, the concept of the platform in the regional innovation system, which reflects specific abilities of regions to connect and combine diverse sources of knowledge, reveals superior local capabilities to explore new technological domains (Harmaakorpi & Melkas, 2005). Platforms as capabilities to develop technological knowledge that wide-open opportunities to technologies and market expansion (Kim & Kogut, 1996; Kogut & Kulatilaka, 2001). According to Kim and Kogut (2006), for firms in high technology industries, such platforms rely on the ability to combine scientific domains, technological fields and related competitive knowledge (Kim & Kogut, 1996).

In this paper, we apply the concept of platform to understand knowledge creation processes. More specifically, we examine how and what extent regions may provide knowledge platforms contributing to developing local inventors' innovative and explorative capabilities. We further explain the underlying mechanisms that may affect the regional innovative performance.

We propose to consider the concept of regional alignment (RA) as a potential explanation for the effectiveness of knowledge platforms. Regional alignment characterizes potential synergies between complementary and heterogeneous knowledge bases, competencies and skills across local agents. Moreover, regional alignment reflects expertise in sciences,

technologies and businesses that have synergistic effects when combined. Regional alignment enacts knowledge platforms because it reveals knowledge and social networks among academic, business and institutional actors facilitating access to external knowledge and increase absorptive capacities. Therefore, regional knowledge expertise may mitigate the risk and uncertainty of knowledge creation.

Our empirical setting relies on European patent and bibliometric datasets to construct regional alignment indicators from 1990-2015. We find a positive relationship between regional alignment and innovative performance. Beside, regional alignment has a positive effect on explorative activities of local inventors or firms. Moreover, regional alignment has a negative coefficient with the rate of exploration and a positive coefficient with forward citation-weight of explorative patents. The results show that regional alignment provides local actors with higher explorative capabilities to search and evaluate the distant knowledge. Therefore, it helps to reduce variance and increase the usefulness of their explorative innovations. Thus it confirms the idea of regional alignment as a knowledge platform that plays a vital role in inventive regional capacities.

This paper contributes to the literature of economic geography by examining the mechanism underlying the process of knowledge generation in the regional specific context. More specifically, our patents for all French regions are tracked for a long period and at fine-level of territory- NUTS3. It helps us to speak at the level of individual inventors and organizations because we consider patenting activities at the regional level that inventors play the majority role rather than the company. Therefore, we could take the address of the inventors to allocate the geographic location of innovation creation process because inventor location is a reliable proxy to indicate where innovation was developed (Ter Wal, 2013). However, the

innovation processes must be approved and financed by the inventor's organizations because more than ninety-five per cent of our patent data has the name and address of organizations.

Second, the unique datasets of scientific publications and patents of all NUTS3 regions set us apart from the prior studies that predominantly rely on the occupation of employees to defining the regional knowledge bases. The scientific publications help us to construct the scientific knowledge bases over time, which we take the affiliation's address of the author and allocate their address at NUTS3 level. As a result, regional technological and scientific knowledge expertise are constructed at the fine-grained NUTS3 level, we suppose that both individual and professional relationships are easily formed rather than at the aggregate NUTS2 level.

Taken together, the French patents and scientific publications at NUTS3 level, the datasets facilitate us not only to construct the regional technological and scientific knowledge expertise but also to observe their interdependencies over time. This dynamic relationship may guide local inventors toward a fruitful search direction and knowledge creation. By using the patent data, we can track up the scientific publications claimed by inventors in their application documents. This relationship helps to create the linkages between technologies and sciences from 1990 to 2015. At the national or international level, these linkages prevail general map of dynamic interdependencies between science and technology, which facilitates local inventors to identify potential knowledge domains. At the regional level, relying on the current expertise of regional knowledge bases, which comprise of both technological and scientific knowledge, local agents can mitigate the uncertainty and cost for search and acquisition new knowledge.

This study also speaks to the literature of innovation management. While the current studies emphasizes the localized knowledge sources that inventors can search for (Gittelman and Kogut 2003; Jaffe and Trajtenberg 1996; Zucker et al. 2007, 2002), scholars still do not

know which scientific knowledge inventors build on and how the role of the geographically distant knowledge is to local inventors<sup>21</sup>. We suggest that the regional knowledge expertise and its potential synergy to other counterparts of scientific knowledge at the aggregated level facilitate local inventor the direction of their search. Therefore, they might have an appropriate strategy to acquire and to combine the new knowledge.

The remaining of the paper is structured as follows. Section 2 reviews the literature on knowledge search and explains the concept of regional alignment. Section 3 describes data sets, measurement, and model specifications. Results are displayed in section 4. In section 5, we discuss the findings and suggest the implications.

## **Literature**

### Search for new knowledge

The invention is as the outcome of a combinatorial search between existing or new knowledge components (Dibiaggio, Nasiriyar, & Nesta, 2014; Fleming & Sorenson, 2001; Nelson & Winter, 1982; Schumpeter, 1934). Knowledge components represent technological knowledge elements used in isolation or in combination with other elements to provide a useful technological solution (Fleming, 2001; Fleming & Sorenson, 2001). Inventors search technological solutions by experimenting with potential combinations of available components and selecting most useful ones, promising higher valuable solutions (Fleming, 2001; Henderson & Clark, 1990; Nelson & Winter, 1982). The combinatorial search reveals complementarities and interdependence across components. Effective associations of components create a social representation of mutual dependence that influences subsequent inventors' combinatorial choice

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<sup>21</sup> Exceptional study of Bikard and Marx (2019), they show that geographic hubs play the role of the bridge between academic and corporate technology, which facilitates the flow of knowledge across them. In our study, the flow of knowledge is out of our scope.

in similar or related contexts (Fleming & Sorenson, 2001). However, the level of interdependence increases search complexity because any novelty at the solution level may affect the effectiveness of components in interaction (Fleming & Sorenson, 2001; Krugman, 1994).

To cope with the complexity of the search space, prior literature has explained that inventors are rationally bounded, thus tend to conduct local search along a technological trajectory by experimenting solutions in the neighborhood of well-known combinations (Cyert & March, 1963; Katila, 2002; Katila & Ahuja, 2002; Stuart & Podolny, 1996). Local search, or exploitation, translates the propensity of inventors to recombine from familiar components or to refine familiar combinations, thus reinforcing path dependency in experimentation (Fleming & Sorenson, 2001; March, 1991; Nelson & Winter, 1982).

While local search facilitates predicting the usefulness of combinations, reduces search uncertainty and failures, and hence increases inventive performance, it also reduces the long-term invention capabilities (Ahuja & Katila, 2004; Kogut & Zander, 1992). Inventors, focusing on cognitive and social representations of useful combinations, may experience a competency trap and thus, limit their exploration capacities (Levinthal & March, 1993; Levitt & March, 1988). Moreover, relying on readily available components may exhaust useful sets of combinations of elements in the neighborhood of already available solutions and be trapped into a technological lock-in and prevent them to engage in distant search and explore useful new components (Ahuja & Katila, 2004; Cohen & Levinthal, 1994; Nelson & Winter, 1982).

Search for new knowledge is also geographically bounded (Phene et al., 2006). Regions provide specific learning conditions for inventors. Relying on local institutions, and learning infrastructures, networks, and concentration of R&D dedicated to similar or related activities, inventors have a privileged accessed to useful knowledge (Feldman, 1994; Feldman & Florida,

1994). Such resources generate regional capabilities that reduce learning efforts of inventors to acquire new, complex, and often tacit knowledge. Then, inventors tend to rely on familiar knowledge networks and contribute to reinforcing the regional specific knowledge base (Neffke, Hartog, Boschma, & Henning, 2018). While this cumulative process generates increasing returns in search efforts, the technological environment may render local knowledge-based obsolete, thus reduces the value of potential combinations of knowledge components available in the region (Glaeser, 2005). For example: Boston sailing ship technology made obsolete by steamship technology in the 19<sup>th</sup> century.

In order to rejuvenate their knowledge base, one of the most effective strategies is to search complementary knowledge coming from different technological contexts, different application contexts, or different geographic context (Afuah & Tucci, 2012; Ahuja & Katila, 2004; Phene et al., 2006; Von Hippel, 1994). Searching technologically and geographically distant knowledge sources for new knowledge are common strategic choices (Jaffe, Trajtenberg, & Henderson, 1993; Phene et al., 2006; Stuart & Podolny, 1996). Particularly, investing overseas helps in increasing knowledge diversity, which proves valuable to inventors (Cantwell & Janne, 1999). Besides, international diversification may increase the awareness for inventors to realize new potential knowledge that is far from their established knowledge domain (Ahuja & Katila, 2004).

The literature also has emphasized scientific knowledge as a source of knowledge base rejuvenation (Ahuja & Katila, 2004; Fleming & Sorenson, 2004). Scientific knowledge acts as a map for inventors searching new knowledge because science aids to understanding the underlying technological problems, to link problems with potential technological options, and to define the path and space of search (Nelson & Winter, 1982). Ahuja and Katila (2004) explain that science also may increase the numbers of knowledge elements that are available for

combinations and helps inventors to understand the underlying properties and the cause-effect relationships across knowledge components, which lead to a better combination (Lippman & McCall, 1976). Hence, not only science can contribute to enrich the knowledge base but also help ruling out unfruitful directions of solution space, predict possible interactions between coupled knowledge components, and reduce the variability of inventive outcome and, thus, directly move to the highest peaks of the landscape.

However, strategies used to searching beyond the established knowledge base comes as a cost for inventors. Learning costs arise when inventors search for external knowledge sources. More specially, it is information processing or imitating costs. The variation of these costs depends upon the quantity and the characteristics of the underlying technological and scientific knowledge of knowledge to be assimilated (Cohen & Levinthal, 1989). Moreover, geography also causes barriers and risks to assimilating and acquiring new knowledge. Knowledge is contextually and locally embedded so that spillovers may fail for two interrelated reasons. First, the characteristics of tacit and complex knowledge make difficulties to unbundle from its context (Kogut & Zander, 1992; Sorenson, Rivkin, & Fleming, 2006). Second, the barriers to communication due to the lack of shared language and the lack of trust among inventors from different communities may cause difficulties in transmitting knowledge (Von Hippel, 1994).

#### Regional alignment as a platform

Regional alignment is the extent to which there are the regional synergies of shared and complementary knowledge expertise (e.g. science and technology), competencies and skills across local agents. Regional alignment implies the interdependencies across knowledge bases, the interactive learning of local agents, and the property of dynamics. First, regional alignment represents the mechanism of knowledge spillovers and interactive learning across inventors, which demonstrate distributed knowledge networks in the region. For example,

inventors/organisations in food and beverage industries (predominantly drawing on an engineering, technological knowledge base for their inventions) may diversify into nutrition products based on knowledge inputs and competencies either from biotechnology firms or/and bio-science results of their co-located universities. This example shows how regional alignment facilitates knowledge spillovers across complementary knowledge bases and competences in a value chain of knowledge. The study shows that innovations may occur when there is knowledge transmission across related industries (Frenken, Van Oort, & Verburg, 2007).

Second, regional alignment acts as a platform. Regional platforms, which are as the configuration of technological and scientific knowledge bases and competencies, generate a set of resources to permit local inventors to choose the optimal strategy of inventions in order to respond to market opportunities. Put it differently; regional platforms represent the potentials for generating future resources rather than describe the existing resources (Harmaakorpi, 2006). In the complex system of knowledge processes, inventors often consider which search directions they choose and which capabilities are useful for their invention process. They then may anticipate the implications of their inventions in the market context. Changing technology requires inventors to evaluate the costs of change against future rewards. For instance, the decision to adopt new technology to develop a particular product is strongly influenced by the cost and quality of delivered products and by the response of competitors toward this product and its attributes (e.g. price and quality). Therefore, Kogut and Kulatilaka (2001) show that when the environment is complex and unpredictable, the best strategy is to invest the platform that enables firms to correspond to the expectations of environment's evolution rather than predict what going on in the environment. In such circumstance, innovation networks can help local actors to explore the potentials existing in the regional platform (Harmaakorpi, 2006; Harmaakorpi & Melkas, 2005).

However, the investment decision on building a platform at the firm level, which has complementary knowledge bases and competences, is more costly, complex and uncertain than those at regional. First, firms (inventors) are rationally bounded by their cognitions and skills (Simon, 1991). They cannot evaluate and assimilate all complementary new knowledge and skills needed. Second, there are trade-offs in terms of costs and benefits when firms acquire new complementary knowledge. Because assimilating new external knowledge reduces the attention which is available to devote to the task of exploiting current knowledge (Levinthal & March, 1993; March, 1991). By contrast, building up a regional platform is not constrained to those factors facing by inventor/firms. It is possible to claim that regional platform, which is theoretically aggregated all knowledge bases and competences in the region, has a broader and more complementary knowledge base. The regional knowledge bases are comprised of various actors located in a region (firms, technology centers, expertise centers, research centers, education organizations) (Asheim & Gertler, 2005; Harmaakorpi, 2006; Harmaakorpi & Melkas, 2005). Accordingly, regions do not face trade-offs when extending new knowledge bases.

Third, regional alignment co-evolves as a change in the structure of complementary knowledge bases and the patterns of synergies between them. These features play as regional capabilities to create different valuable complementary options for local inventors. Barney (1986) introduces the idea of a scarce factor that core competencies are valuable when they are applied and useful for future applications. His study posits that core competence is as a scarce factor because it embeds complex options on future opportunities (Barney, 1986). Diericks and Cool (1989) add a property of irreversibility by emphasizing the arrow of time. That knowledge and competencies are built over time and firms will earn their “excess rents” through their organizational complementarities (Kogut & Kulatilaka, 2001). This notion can help to explain the concept of regional alignment. Particularly, due to the characteristic of cumulative and

complementary knowledge bases in the region, the knowledge structure of which always changes along a technology trajectory (Dosi, 1982; Quattraro, 2016). Accordingly, the patterns of the synergies between science and technology also vary, which indicates the evolutionary structure of the knowledge platform in the region. The evolution of regional alignment may affect the ways and the types of knowledge which are generated and diffused in the region. As a result, the regional platform may generate future optional opportunities (in terms of technology and science) that favor to local inventors not only to assimilate new knowledge but also to have potential market application for their inventions.

### Regional alignment and innovation performance

Regional alignment allows inventors to predict the outcomes of their inventive search. When inventors want to acquire new knowledge, which is far from their used domains, they may estimate the costs its acquisition as well as predict a future value of acquired knowledge elements (Cohen & Levinthal, 1990; Kogut & Kulatilaka, 2001). However, these estimations are relatively coupled with an uncertain property of and the asymmetric information of new knowledge (Gallini & Wright, 1990). Besides, time for searching optimal solutions is finite; thus, search processes often lead to non-optimal decisions. The acquired knowledge does not represent the 'best' one because solutions for many problems are not computable (Simon, 1969). Some technologies might have potentials on the wide range of market applications while other technologies are specifically applied to certain markets and have dead-ends for further development (Kim & Kogut, 1996). Regional alignment may facilitate local inventors being aware of certain potential technologies, which in turn enable them to envisage the sources of complementary knowledge and competencies. This is because, through the co-location of similar activities, local firms may acknowledge successful experiments done by other firms (Boschma, 2004). Also, regional alignment helps local actors identify themselves on the

regional knowledge platforms. Therefore, local inventors may position potential combinations among diversified and complementary knowledge sources.

For instance, the ICT cluster in Sophia-Antipolis has launched its regional knowledge platform that enables local firms to deliver innovations which have market opportunities. Members comprise of local development institutes, clubs and associations, research institutes and telecom standards institutes, consultants and local ICT firms. Those firms represent the telecom value chain (such as internet access and service providers, the value-added resellers, distributors, the content providers, the network operators and telecom service providers, the terminal device manufactures, the network infrastructure providers and the application developers). Such the platform helps to map an identification of each local firm on the knowledge value chain. It also enables them to find appropriate competencies and suitable partners, to share resources to exploit complementary knowledge better, to gain better understand the partners' need in order to define their internal competencies as well as to create a shared vision of the current and future market (Lazaric et al., 2008). More than just the sum of the innovation capability of local actors, the regional platform also reflects the synergy effects of combining a variety of knowledge sources (Harmaakorpi, 2006). The synergy benefits local firms by accessing to the heterogeneous sources of information in order to combine and recombine various resource configurations.

Additionally, regional alignment generates interactive and collective learning, which enable local inventors to overcome the barriers of knowledge spillovers in order to acquire new sets of knowledge, resources, competencies and skills. The tacit and idiosyncratic nature of knowledge generally requests the share of the common language, face-to-face interaction and mutual trusted understanding in order to gain effective transfers (Howells, 2002; Von Hippel, 1994). The fact is that social networks are generally localised, hence knowledge is

geographically transmitted through networks (e.g. community of practice) (Breschi & Catalini, 2010; Ter Wal, 2013). The essential characteristic of the network is the distribution of knowledge that members continuously learn each other.

Regional alignment also reflects its capability to create and manage knowledge in a collective and cumulative learning process, which provides both as incentives and opportunities for further assimilation of knowledge, competencies, and skills (Boschma, 2004; Harmaakorpi & Melkas, 2005). The knowledge platform enhances the emergence of collective identity by reinforcing actors' commitments on the community and by making sense of the logic of their actions (Lazaric et al., 2008). As a result, the difficulties and barriers significantly reduce when local inventors access distant knowledge in the regional platforms.

For instance, in 2005, firms and organizations operating in the Provence Alpes Cote d'Azur region collaborated to launch the user-oriented project, which combined complementary competencies among local actors, to participate in the national project of “poles of competitiveness”-in the Solutions Communicantes Sécurisées pole (Lazaric et al., 2008). The evidence illustrates the role of regions by creating a platform of complementary knowledge and competencies, which help local actors to improve their abilities to detect the opportunities as well as to anticipate the value of innovative collaborations.

Besides, a regional platform acts as selection mechanisms, which allows knowledge creations based on long-term strategy. For example, Telecom Valley in Sophia Antipolis has launched the project of regional knowledge platform. Primary objectives are to map all competences on the region, to identify actors and projects as well as to facilitate collaborations. Then, Sophia Antipolis MicroElectronics (SAME) association was set up with the mission of reinforcing R&D policy within the microelectronics sector. Telecom Valley had perceived that the new associations would create an overly fragmented new division of labour with the existing

cluster, which might hinder interactions in the region currently. To solve this problem, the meeting was organized to distinguish the different role of each actor. Such that SAME mainly plays a vital role by promoting technological innovations, while Telecom Valley acts the role of orienting markets and future uses of some product innovation (Lazaric et al., 2008). This example evidences that are effectively utilizing of regional knowledge platform can help to structure cluster's networks by defining their specific role either in supporting knowledge combination or in orienting market and long-term strategy of local firms. As a result, local inventors, who have specific required skills and are in the local networks, may have a better visualization of complementarities and potential markets.

Regional alignment as a platform helps to reduce the screening and adoption cost, thus increases the likelihood to explore new potential capabilities. In organization behaviour, Dosi and Kogut (1993) propose the correspondence of technologies and organization indicates complementary relations, which is difficult to separate each other. It implies that changing to new technology requests a change of organizational structure (Dosi & Kogut, 1993). Therefore, exploring new distant technology may induce the switching cost of between sets of technological and organizational components. The cost comprises of technological and organizational learning costs (Kogut & Kulatilaka, 2001). It is hardly estimated because the entry cost generally relies on the value of other firms operating in the current market.

For example, a pharmaceutical firm wants to enter biotechnology. The price of biotechnology firms does not give the value of the core biotechnological capability that the pharmaceutical firm has to pay for entry, because the cost for entry is idiosyncratic to each biotechnology firms. However, the price of biotechnology provides information as an estimated factor (e.g. risk) that acts as optional value to enter in this market. The cost of altering a tightly coupled technological and organizational set may hinder inventors to explore new technology

when they compare with the current net value of their existing technology. Regional alignment as a platform helps inventors to identify and evaluate a potential set of technological and organizational capability in among sets of alternative options presenting in the region. Adopting a new set of organizational and technological element capability, which is aligned to the current core competence of inventors/firms, will significantly reduce the switching cost of assimilating distant technology because core competence allows inventors choose an optimal strategy for their investment (Kogut & Kulatilaka, 2001). As a result, it may increase the quality and potential of acquired technology.

For instance, R&D inventor working in a food firm may use biological materials for their inventions. By definition, any treatments of food are as an application of biotechnology. If there are existing biotechnology, agriculture, food chemistry technologies in the region, inventors have many alternative options where he/she can assimilate that knowledge. Among those options, biotechnology may be the best one for them because they have a certain level of knowledge on this technology. Hence, the switching cost will be the lowest in compare the others. By acquiring biotechnology, firms will have opportunities to diversify into organic products in the short term or beer/wine products in the long term because biotechnology is increasingly used in those products for enhancing innovative products.

Therefore, we expect the regional alignment helps local inventors to identify and acquire valuable information and knowledge, which increases the usefulness of their inventions.

Hypothesis 1: the regional alignment has a positive correlation with innovative regional performance.

### Regional alignment and explorative performance

Innovation literature classifies different innovation's performance, which comprises of the exploitative and explorative invention (March, 1991). The exploitative invention refers to refine, reselect and recombine previously used knowledge elements. Therefore, the value of the recombination process remains stable. Meanwhile, explorative activities are more likely to involve new experimentation and take a risk. Each type of inventive activity requires inventors/firms having different strategies for the innovation creation processes. These processes comprise of realizing the knowledge elements and of combing them together. Such processes may differ from one project to another if the properties of individual knowledge elements and its relational combinations change (thus, the value of combination) (Dibiaggio et al. 2014).

Since the relational properties of knowledge evolve and vary, local actors are lack of ability to predict the outcome of new combinations. As Yayavaram and Ahuja (2008) suggest, when firms experiment with new combinations, they must be exposed to new beliefs about the relational properties of knowledge element. As a result, the value of the explorative invention is unpredictable. The regional knowledge expertise may significantly affect its capacity to explore the potential new knowledge elements. However, this benefit does not guarantee that their explorative activities are fruitful. Therefore, scientific knowledge is a valuable source to project new distant combinations that are far from the current technological trajectory (Ahuja and Katila 2004; Fleming and Sorenson 2004).

First, the region should themselves identify their technological knowledge expertise in compared with other regions. Then they may map the pattern of interdependence across their current technologies with different potential related scientific fields because specific technology will have the synergistic effect on the particular scientific field as it is combined.

The regional alignment provides fruitful combinations across different technologies and sciences at the aggregated national level. However, the overall picture of different combinations will be more verified if it is guided science. Indeed, science reduces redundant effort and increases the efficiency of research activities (Nelson 1959). On the other hand, the multifaceted interactions between science and technology reveal the useful direction of search for knowledge (Meyer 2000).

If the potential knowledge is residually located in the region as its scientific expertise, regional alignment and the oriented-science significantly reduces cost and delay-time for local actors to evaluate access and acquire new distant knowledge through knowledge externalities. We expect that the regional alignment helps inventors not only increase their explorative patents, but also carefully select explorative projects, thus increase its value.

*Hypothesis 2a:* the regional alignment increases the explorative patents in the region.

*Hypothesis 2b:* the regional alignment reduces the rate of exploration.

*Hypothesis 2c:* the regional alignment increases the value of explorative patents in the region.

## **Data and research methods**

### Data and sample selection

The key dependent and independent variables rely on 743,693 French patents granted by the European Patent Office from 1990 to 2015, retrieved from the PATSTAT database (version fall 2015). Each patent provides information about the application year, the priority year, the publication year, the inventors of the patent, and citations to patents previously granted or to non-patent prior-art references (NPRs).

To test our hypotheses, we built a panel dataset combining all regional technological and scientific characteristics and related references to scientific work. Most of the previous studies use the published (granted) year of patents as a time for their observed periods (McMillan et al. 2000; Narin et al. 1997; van Vianen et al. 1990). This chapter applies the priority year of patents to construct the period of observations because that year is as the specific time when the patent activities are carried out.

### ***Data to construct the regional technological knowledge expertise***

Among 743,693 patents, there are only 114,244 patents that have information about the address of inventors (such as zip code, city name). Inventor's location is a reliable proxy to indicate the place where innovation was developed (Ter Wal, 2013; Leten et al., 2014). If there are many inventors of a patent claiming in the same region, we record only one observation for that region. At the aggregated level, the sum of total patents in a region also reflects its technologies. Therefore, we discard the locations of patent's applicants (or assignee) because these are often the headquarters' addresses rather inventors' location. Technological characteristics of patents are based on the International Patent Classification (IPC) which assigns each patent to one or several pre-define technological classes<sup>22</sup>. We use the last version of the IPC<sup>23</sup> consisting of 35 technological classes (Schmoch 2008). This technology classification allows us to measure regional knowledge in each technology domain yearly.

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<sup>22</sup> There are other classification systems available such as the US Patent Classification (USPC), the Cooperative Patent Classification (CPC). They differ in the level of granularity and pre-define association to patent applications. Concordance tables are available but imperfect. They all have interests and disadvantages. Comparing IPC and USPC, Harris, Arens, and Srinivasan (2010) show that USPC has a far tighter focus (163,000 entries compared to 71,000 for the IPC) and provides better information on the invention's true purpose by being more precise about technologies used in patents. However, as a result of greater granularity, USPC proves much less effective in covering a large variety of patents. Therefore, we selected the IPC system to be able to include more diverse patents in the analysis.

<sup>23</sup> IPC has been updated through a collaborative work between the German Fraunhofer ISI, the French Observatoire des Sciences et des Technologies (OST) and the French patent office (INPI).

### *Data to construct the regional scientific knowledge expertise*

To measure regional scientific expertise in each specific domain, we collected all scientific articles published by French authors<sup>24</sup> and assigned them to a pre-defined scientific domain. More precisely, we extracted 1,481,784 scientific articles published by a French author between 1990 to 2015 from Thomson Reuters' Web of Science (WoS). Then, relying on the academic journal where it has been published, each paper was then assigned to one of the 22 scientific domain as provided by the Science-Metrix journal classification (Archambault et al. 2011). Several journal classifications are available and used by the literature or by research assessment bodies. Science-Metrix classification (SMc) used several established classification systems to create a unique taxonomical tree<sup>25</sup>. The advantage of SMc is its extensive coverage of academic journals including journals reported in Scopus and Web of Science (WoS) lists. Science-Metrix classification assigns each individual journals to single, and mutually exclusive categories. Although publications and authors' activity increasingly rely on interdisciplinary work and may be assigned to several scientific fields or subfields (Glänzel and Schubert 2003), the allocation to several fields or subfields may create ambiguous information and prevent consistent comparison exercises (Gómez et al. 1996). Then, using the postcode of the address of the author's affiliation, each paper was allocated to a French region. Similar to the geographic allocation of patents, co-authored papers may have been allocated to several regions if co-authors work in different regions.

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<sup>24</sup> Authors affiliated to a French university, public or private research institution or corporation.

<sup>25</sup> To associate journals and with research fields and subfields, Science –Metrix used the new US NSF classification, -based on the Computer Horizons Inc. classification (CHI), initially designed by Mark Carpenter and Francis Narin in the 1970s-, the WoS classification managed by Thomson Reuters, the Evaluation of Research Excellence (ERA) classification designed by the Australian Research Council, the revised Field of Science and Technology (FOS) Classification in the Frascati Manual, and the European Research Council (ERC) classification. The list is freely accessible under a creative commons science ([www.science-metrix.com](http://www.science-metrix.com))

## *Data to construct the interdependence between different types of scientific and technological knowledge expertise*

Following prior literature, we used non-patent references (NPRs) cited in patent data. Then, we created dyads between each patent and the NPRs cited on the front page of the patent (Ahmadpoor and Jones 2017; Bikard and Marx 2018; Cassiman et al. 2018; Fleming and Sorenson 2004; Meyer 2000; Narin and Breitzman 1995). Among the 743,693 patents collected, we found 100,377 patents citing 275,951 NPRs.

NPRs are prior-art citations of various sources, such as books, Internet, or patent granted by the Japanese office that are not necessarily related to scientific work. A simple count of NPRs may be an ambiguous and imprecise measure of the use of scientific references (Cassiman et al. 2008). To overcome the risk of constructing a noisy dataset, we only selected references of articles published in scientific journals. This is a very conservative strategy since it excludes several scientific sources such as books and conference proceedings. Identifying scientific publications in the list of NPRs is challenging because each information (such as title, journal name, volume and issue number, authors' name, year of publication, etc.) are sometimes missing or, when included, truncated or misspelled. Furthermore, scientific references are recorded as unstructured information often grouped in the same cell, and not necessarily in a systematic order, thus increasing the computational challenge. To exploit such unstructured data, we developed an algorithm using Google scholar search engine to identify and extract the title of the article, the academic journal where the article has been published, the year of publication, and the geographic location of the authors. We obtained 26,068 patents citing 61,486 scientific articles published in 15,012 academic journals. The dataset helps to construct the linkages between scientific domains and technological fields.

## **Key variables**

### Dependent variable

#### ***Forward citation-weighted patents***

We use a patent's forward citation as an indication for patent quality (Dibiaggio et al., 2014; Fleming & Sorenson, 2004; Pavitt, 1988). Innovative performance is implied by the number of prior art citations that each patent received during the first five years after it was granted (Trajtenberg 1990). In this paper, we calculated the innovative regional performance as the total forward citation counts for region  $i$  at time  $t$ .

#### ***Explorative innovative performance***

Explorative inventions happen when inventors attempt a new combination (Dibiaggio et al., 2014). We consider two types of explorative invention. First, explorative invention characterised to recombination's exploration if it introduces a technological combination that is new to the region within the last five years. Second, explorative invention characterised to distant search's exploration if it introduces a new technological subclass that is new to the region within the last five years.

There are three dependent variables regarding the explorative invention. First, the *number of explorative patents* is granted to a region in year  $t$ . Second, the *explorative rate* describes the extent to which a region introduces explorative inventions relative to its total inventive activities. The number of explorative patents in the total patents indicates the rate of a region's explorative inventions. The indicator implies the exploration intensity of a region's inventive behavior. Last, the *forward citation-weighted explorative*

*patents* are the number of times that explorative patents have been cited in subsequent patents within the first five years after it was granted.

#### Independent variables

To smoothen the trend of variables, we sum their value over the past five years to calculate the regional yearly variables. Then, these aggregated values are used to construct individual variable in year  $t$  in a region. For example, the number of publications in the domain ( $j$ ) in year  $t$  in a region is:

$$P_{jt} = \sum_{t=0}^{t=4} P_{j_{t-1}} \quad (1) \quad \text{where } t = \{1994, \dots, t, \dots, 2009\}$$

#### ***Regional alignment (RA):***

The objective of *RA* is to estimate the potential of synergistic relations between scientific, technological and industrial resources in a region. We suggest that this potential may contribute to the competitiveness of local firms and regional economic performance if the focal region can demonstrate expertise (a high level of specialisation relative to other regions in the country) in those synergistic resources. In this paper, *RA* only relies on the potential synergies between scientific and technological expertise which result in regional platforms. The estimation of *RA* of a region is a three-step process.

First, we consider the yearly level of synergies between technological fields and scientific domains at the national level. This measure reveals the intensity of the combined use of each technological field and scientific domains in French patents. More precisely, the level of synergy between the technological field ( $i$ ) and scientific domain ( $j$ ) results from the intensity of citation of scientific papers in the domain ( $j$ ) by patents associated with the technological field ( $i$ ). For instance, the "analysis of biological materials" has cited more papers in

"Biomedical research" or "Clinical Medicine" than papers published in journals associated with "Earth & environmental sciences". Conversely, patents using "Audio-visual Technology" never cite papers in "Biomedical Research" journal and is rather exploiting scientific results in journals specialised in "Information and Communication Technologies", "Physics and Astronomy" or "Mathematics and Statistics". Notice that some combinations are very stable over time (e.g. "Chemical Engineering" and "Chemistry"), whereas others, such as the relation between "Computer Technology" and "Clinical Medicine" or "Biomedical Research", evolve from independent until the late 1990s, to levels of citation as high as "Engineering" or "Physics and Astronomy" or even "Information and Communication Technologies" for "Clinical Medicine" (in the 2000s).

The level of synergy between each couple of technological field ( $i$ ) and scientific domain ( $j$ ) is captured by the indicator  $\lambda_{ij}$  which can be estimated by parametric measures. In a parametric setting, it is assumed that a random combination between ( $i$ ) and ( $j$ ) follows a hypergeometric distribution.

$$\lambda_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \quad , \lambda_{ij} \in R \quad (2)$$

where  $J_{ij}$  is the actual number of observed co-occurrences between two technology ( $i$ ) and scientific field ( $j$ );  $\mu_{ij}$  is the expected (mean) value of a random technological co-occurrence and  $\sigma_{ij}$  is the standard deviation. Thus if  $J_{ij} > \mu_{ij}$ , then technology  $i$  and scientific domain  $j$  are highly related. Conversely, when  $J_{ij} < \mu_{ij}$ , then  $i$  and  $j$  are quite independent. Finally, we normalized RSE to be bounded between 0 and 1 as follows:

$$\lambda'_{ij} = \frac{\lambda_{ij} - \text{Min}\lambda_{ij}}{\text{Max}\lambda_{ij} - \text{Min}\lambda_{ij}} \quad (3)$$

We used the well-known relative –or revealed- comparative advantage that has been used to measure technological expertise (Archibugi and Pianta 1994; Malerba and Montobbio 2003) or national product specialization in international trade (Dalum 1999; Hausmann and Hidalgo 2011). This variable indicates for every region the relative share of forward citations in a specific domain compared to the share of total forward citations in this domain at the national level. More precisely, the technological expertise of region  $r$  is measured as follows

$$RTE_{ir} = \frac{\sum P_{ir} / \sum P_r}{\sum P_{iN} / \sum P_N} \quad (4)$$

where  $P_{ir}$  is the total forward citations that the technological field ( $i$ ) receive within 5-year in the region ( $r$ );  $P_r$  is total forward citations that the region ( $r$ ) receive within 5-year since that technology ( $i$ ) existed in the region;  $P_{iN}$  is total forward citations of the technological field ( $i$ ) receive within 5-year at the national level, and  $P_N$  is total forward citations in France.

We further follow the same logic (as  $TRE$ ) to calculate the regional expertise in each scientific domain ( $RSE$ ). This variable indicates for every region the relative share of scientific publications in a specific domain compared to the share of publications in this domain at national level. More precisely, the scientific expertise of region  $r$  is measured as follows

$$RSE_{jr} = \frac{\sum P_{jr} / \sum P_r}{\sum P_{jN} / \sum P_N} \quad (5)$$

where  $P_{jr}$  is the total number of scientific publications in the domain ( $j$ ) in the region ( $r$ );  $P_r$  is the total number of scientific publications in the region ( $r$ );  $P_{jN}$  is total number of French publications in domain ( $j$ ), and  $P_N$  is the total number of publications in France.

Finally, we define the yearly *RA* of each region as the sum of regional alignment in each combination (*i*) and (*j*). For each couple technology field (*i*) and scientific domain (*j*), the regional alignment is defined as the interaction between the regional technological expertise in (*i*), the regional scientific expertise in (*j*) and the level of interdependence between (*i*) and (*j*).

$$RA_{ijr} = \lambda_{ij} * RTE_{ir} * RSE_{jr} \quad (6)$$

where  $RA_{ijr}$  is the regional alignment of a region (*r*) in technology (*i*) and scientific domain (*j*). Then, the regional alignment of a region (*r*) is

$$RA_r = 1/n * \sum_{ij} RA_{ijr} \quad (7)$$

***Control variables:***

*The Intensity to cite patents within region.* We control for regional knowledge sources, which are valuable to local inventors on their innovative activities (Jaffe et al., 1993). To measure the knowledge sources, we consider the patent's portfolio in the region at the time (*t*) and check backward citations (cited patents) made by the focal region's inventors in the five years prior to year (*t*). The total backward citations are used as the denominators for our regional knowledge sources variable. We next classify whether inventors of cited and citing patents are located in the same region. The total number of backward citations of patents inventing by other inventors (except the self-citations) in the region is as the numerator for our regional knowledge sources.

*Regional R&D expenditure.* Due to available data of R&D expenditure at NUTS2 level, we calculate R&D expenditure at NUTS3 level by share of the regional population at the aggregated NUTS2 (SOURCE OF DATA: Eurostat, 2019). A region with a larger population will take a larger share of R&D expenditure. Then we average R&D expenditure of regions

over the period. We slit regions into three groups, such as low R&D expenditure regions (less than 100 million euros per year), medium R&D expenditure regions (yearly R&D expenditure ranges more than 100 to smaller than 1,000 million euros), and high R&D expenditure regions (greater than 1,000 million euros).

*The coupling.* Following to Fleming and Sorenson (2004), we control for the difficulty of the inventive problem in the region. At the patent level, the *coupling* indicates the degree of coupling among the knowledge components. This variable mainly observes the degree to which an invention's components have been previously recombined<sup>26</sup>. We build this measurement in two steps. First, we observe the ease combination of the subclass (*i*) used in a patent (*j*). It is measured by calculating the numbers of combinations associated with technological subclass *i* on the number of patents associated with subclass *i*. Second, the coupling is the ratio between the total number of subclasses and the total observed combinations of all subclasses in the region at year *t*. Then, we aggregate the coupling variable at the regional level. At the regional level, the high value of coupling indicates that the region deals with the high complexity of invention activity.

*The number of technological classes in the region.* This variable control for technological diversity in the region by the total aggregating number of main classes in a region. The regional knowledge platform comprising of a wide range of technologies may have advantages on approaching different technological knowledge field. Thus, it may enhance the potential recombination for future inventions.

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<sup>26</sup> Refer to Fleming and Sorenson (2004) for more details

### Model specification

Innovative performance is a count variable and takes on only nonnegative integer values. Poisson regression is generally applied to model count data (Hausman, Hall, & Griliches, 1984). To count for over-dispersion data, we use a fixed effect negative binomial regression (Ahuja & Morris Lampert, 2001; Dibiaggio et al., 2014; Fleming & Sorenson, 2004).

$$E(y_{rt} | X_{rt}) = e^{\beta X_{rt}}, \quad (8)$$

where  $y_{rt}$  is the citation-weighted patent counts for the region ( $r$ ) at time  $t$ ;  $\mathbf{X}$  is the explanatory vector of variables (including our interest variable), and  $\beta$  is the vector for the parameters of interest.

Regarding the dynamic panel data, we apply a panel dynamic fixed effect model (Wooldridge, 1999, 2010). Hence, all explanatory variables are one-year lagged in time and logarithmic transformed, except for the lagged dependent variables. Because all explanatory variables have a minimum value of zero, they are added a value of 1 before the logarithmic transformation. Therefore, the estimated coefficients of the transformed variables can be interpreted as elasticities (Wooldridge 2010).

$$E(y_{rt} | Y_{rt-1}, X_{rt}) = e^{(\delta Y_{rt-1} + \beta X_{rt})}, \quad (9)$$

where  $y_{rt-1}$  is forward citation counts of the region ( $r$ ) at the time ( $t-1$ ). We also add the variable year to control for changes that may affect the regional technology overtime. In addition to these variables, all regression models include regional fixed effect to control for any residual unobserved heterogeneity between regions.

While France is composed of 101 regions (NUTS3 level), the missing data in some regions reduces the dataset to 93 regions. All explanatory variables are aggregated for five-backward years window, and dependent variables (i.e. *forward citation-weighted patents and forward citation-weighted explorative patents*) are counted for five years since patents were granted. Within French patent dataset (1990-2015), we could create panel data to observe 93 regions from 1994 to 2009.

Table 3.1- 3.2 list the descriptive statistics and correlations for all variables. The mean weighted forward citations equal to 107, with large differences across regions (the standard deviation of 434). The regional alignment correlated positively to the value of innovation (forward citation-weighted both exploitative and explorative patents). Addition, there is a high correlation between numbers of technological subclasses and R&D expenditure (0.733). We address this problem by estimating the expected technological class for regional R&D expenditure. We then compute the difference between the observed and expected technological class based on R&D expenditure. Finally, we use different value in the regression models.

	Obs	Mean	Std. dev.	Min	Max
Forward citation-weighted patents	1488	107.11	434.07	0.00	6,176.00
Number of explorative patents	1488	21.67	33.34	0.00	305.00
Exploration rate	1488	0.41	0.21	0.00	1.00
Forward citation-weighted explorative patents	1488	26.76	83.01	0.00	1,344.00
Regional alignment (Log)	1488	1.57	0.47	0.00	3.37
Intensity to cite patents within region (Log)	1488	0.04	0.06	0.00	0.41
R&D expenditure (Log)	1488	5.18	1.06	2.30	8.08
Coupling (Log)	1488	1.56	0.16	0.00	2.12
Number of technological classes (Log)	1488	5.41	0.66	2.30	6.38

Table 3. 1: Descriptive data

	1	2	3	4	5	6	7	8	9
1 Forward citation-weighted patents	1.000								
2 Number of explorative patents	0.824	1.000							
3 Exploration rate	-0.190	-0.289	1.000						
4 Forward citation-weighted explorative patents	0.969	0.837	-0.179	1.000					
5 Regional alignment (Log)	0.008	0.070	-0.136	0.004	1.000				
6 Intensity to cite patents within region (Log)	0.187	0.267	-0.206	0.201	-0.025	1.000			
7 R&D expenditure (Log)	0.400	0.683	-0.358	0.419	0.253	0.177	1.000		
8 Coupling (Log)	-0.112	-0.147	0.007	-0.115	0.110	0.076	-0.129	1.000	
9 Number of technological classes (Log)	0.284	0.558	-0.442	0.318	0.274	0.314	0.733	0.133	1.000

Table 3. 2: Correlation matrix

## Results

Table 3.3 presents the results of the innovation performances in the region. In model 1-6, the dependent variable is forward citation-weighted patents in the region during the first five years after it was granted. Model 1 includes all control variables. Regional R&D expenditure and intensity to cite patents locally have a positive and significant effect. The negative and significant coefficient of the year variable implies a negative time trend in patenting. The positive and significant coefficient of the lagged dependent variable, but the magnitude is negligible, displays no evidence of spillovers from other regions. In Model 2, the variable “regional alignment” is added. Positive and significant effect of regional alignment is found indicating that, regions benefit from the alignment. As expected, the result shows a significantly positive relation between regional alignment and forward citations in the region, which supports our first hypothesis. Because regional alignment is lagged one year in the specification, this implies that the benefits of regional alignment have time-delayed effects. The estimated coefficients of the regional alignment variable can be interpreted as elasticities as a consequence of the logarithmic transformation (Wooldridge 2010). The elasticity for regional alignment 33 percent. It implies that (a change in) regional alignment say of 10% implies a 3.3% change in the technological performance of regions.

We further examine the effects of regional alignment across different levels of R&D expenditure (Models 3-6). The distribution of R&D expenditure is right-skewed, which the mean is greater than the median. Therefore, we split regions into different groups that are below the mean, between the mean and one standard deviation, between the mean and two standard deviations, and above the mean and two standard deviations. The elasticities for regional alignment are compared across these different regions. At first, interestingly, while the effects of R&D expenditure are not significant for the groups of regions spending R&D expenditure above the mean, the positive and significant coefficients are consistent across groups of regions. One may assume that the effect of R&D will be held in a specific regional context. Indeed, Blazek and Kadlec (2018) show that the size and structure of R&D systems have impacts on innovative performances of regions. However, the level of effect also depends on the typology of regions in terms of their innovation performance, such as innovation leaders, strong innovators, moderate innovators, and modest innovators<sup>27</sup>.

The elasticity (8.7 percent) for regional alignment in regions having R&D expenditure between the mean and one standard deviation is significantly higher than other groups of regions (Model 4). This indicates that (changes in) regional alignment have a larger effect on (changes in) regional technological performance. The group of regions having R&D expenditure below the mean is at the least benefits from regional alignment (2.8 percent) (Model 3).

The group of regions in the top-tier of R&D expenditure also gain benefits from regional alignment (Model 6). The elasticity is about 5.9 percent (change in) technological performance. Moreover, the magnitude of the coefficient is at the largest level compared with other groups,

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<sup>27</sup> This study does not examine such a research question. However, we elaborate future research questions relating to this direction in a discussion section.

both the *intensity to cite patents within the region* and the *number of technological classes in the region*. The findings are consistent with the literature of local technological knowledge source (Feldman and Florida 1994; Jaffe et al. 1993). The negative and significant effect of the coupling shows that regional technological performance reduces when local inventors deal with the complex technology.

	Model 1 NB FE	Model 2 NB FE	Model 3 NB RE	Model 4 NB FE	Model 5 NB FE	Model 6 NB FE
	All sample	All sample	R&D below the mean	R&D above the mean		
				Between (mean + 1S.D)	Between (mean + 2S.D)	Above (mean + 2S.D)
<i>Dependent variable: forward citation-weighted patents</i>						
Lagged dept . Variable	0.000141*** (4E-05)	0.000135*** (4E-05)	0.00267*** (8E-04)	0.000906*** (3E-04)	0.000680*** (2E-04)	0.000113** (5E-05)
Regional alignment		0.333*** (0.064)	0.283*** (0.076)	0.877*** (0.262)	0.859*** (0.224)	0.594** (0.293)
Intensity to cite patents within region	0.631* (0.339)	0.805** (0.336)	0.735* (0.396)	1.315 (1.029)	1.351 (0.894)	2.499** (1.008)
R&D expenditure	0.581*** (0.043)	0.576*** (0.044)	0.421*** (0.090)	-0.51 (0.411)	0.268 (0.263)	-0.296 (0.718)
Coupling	0.306 (-0.260)	0.416 (0.260)	1.087*** (0.300)	-1.225 (0.885)	-1.147 (0.843)	-5.058** (2.199)
Number of technological classes	0.0897 (0.287)	0.074 (0.288)	-0.245 (0.302)	2.133 (1.416)	1.647 (1.356)	4.909** (2.431)
Year	-0.111*** (0.005)	-0.125*** (0.005)	-0.110*** (0.008)	-0.0987*** (0.022)	-0.119*** (0.016)	-0.0961*** (0.022)
Constant	219.6*** (9.323)	246.5*** (10.730)	216.6*** (16.710)	202.5*** (41.440)	239.3*** (30.980)	203.0*** (39.620)
Observations	1,395	1,395	1,067	173	212	112
Number of nuts3	93	93	80	21	25	9
Wald Chi2	854.600	867.600	289.100	104.300	167.200	258.800
LL	-5066.000	-5052.000	-3366.000	-694.000	-900.200	-608.600

All independent variables are in logarithm.

All independent variables are lagged one year.

Standard errors in parentheses

\*\*\* Significant at 1%

\*\* Significant at 5%

\* Significant at 10%

Table 3. 3: Negative binomial regression with region fixed-effects. Determinants of innovation's performance

Table 3.4 tests the robust results in different models. In model 7, we run the random fixed effect. We further estimate the regressions by dropping the outliers (e.g. Paris) (Model 8) and two years of observation (1994 and 1995 in model 9). The results remain similar when we estimate different regressions. The findings support our previous conclusions regarding the role of regional alignment.

	Model 7	Model 8	Model 9
	NB RE	NB FE	NB RE
	All sample	Drop Paris	Drop two years
<i>Dependent variable: forward citation-weighted patents</i>			
Lagged dept . variable	0.000134*** (3E-05)	0.000685*** (1E-04)	0.000130*** (4E-05)
Regional alignment	0.354*** (0.062)	0.322*** (0.064)	0.328*** (0.067)
Intensity to cite patents within region	1.000*** (0.333)	0.801** (0.342)	0.706* (0.362)
R&D expenditure	0.652*** (0.042)	0.525*** (0.047)	0.571*** (0.046)
Coupling	0.713*** (0.234)	0.430* (0.260)	0.623** (0.266)
Number of technological classes	0.139 (0.280)	0.0525 (0.288)	0.515* (0.311)
Year	-0.128*** (0.005)	-0.116*** (0.006)	-0.128*** (0.006)
Constant	252.2*** (10.370)	229.5*** (11.620)	253.0*** (11.340)
Observations	1,395	1,380	1,302
Number of nuts3	93	92	93
Wald Chi2	1,025.000	848.400	757.900
LL	-5,741.000	-4,935.000	-4,648.000

All independent variables are in logarithm.

All independent variables are lagged one year.

Standard errors in parentheses

\*\*\* Significant at 1%

\*\* Significant at 5%

\* Significant at 10%

Table 3. 4: The robustness of the results. Testing alternative models

Table 3.5 examines the impact of regional alignment on the explorative invention. Model 10 shows the positive and significant coefficient of regional alignment on the number of explorative patents in regions. The elasticity of regional technological performance on explorative patents is about 2.0 percent with respect to regional alignment. In the model 11, the result of the coefficient is negative and significant for the rate of explorative patents. Put the model 10 and 11 together, the findings imply that regional alignment increases the changes in explorative patents of the region, and induces local inventors carefully select their explorative inventive projects. As a result, the explorative performance will achieve at a high value. The positive and significant coefficients of regional alignment on the performance of explorative patents support our hypothesis (Model 12-16). The elasticities vary between 2.5 and 12.0 percent. These results suggest that regions differ in terms of how regional alignment affects their explorative performance.

The effects of R&D expenditure on the explorative performance of region are positive and significant for the groups of regions (below the mean, and the top-tier R&D investment), with elasticities between 6.2 and 25.7 percent, respectively (Model 13 and 16). No additional effect of regional alignment is observed for the other groups. These findings show that regions with the low-tier and top-tier R&D expenditure mostly benefit from regional alignment.

	Model 10 NB FE	Model 11 Xttobit	Model 12 NB FE	Model 13 NB FE	Model 14 NB FE	Model 15 NB FE	Model 16 NB FE
	Explorative patents	Exploration rate	Forward citation-weighted explorative patents				
			All sample	R&D below the mean	R&D above the mean		
					Between (mean + 1S.D)	Between (mean + 2S.D)	Above (mean + 2S.D)
Lagged dept. explorative patent variable	0.00298*** (0.001)						
Lagged dept. exploration rate variable		0.036 (0.030)					
Lagged dept. forward citation- weight explorative patents			0.000449** (0.000)	0.001 (0.002)	0.001 (0.001)	0.001 (0.001)	0.000 (0.000)
Regional alignment	0.206*** (0.040)	-0.0351*** (0.013)	0.388*** (0.079)	0.250*** (0.094)	1.181*** (0.336)	1.207*** (0.292)	0.507* (0.298)
Intensity to cite patents within region	-0.358* (0.197)	-0.213** (0.091)	0.073 (0.432)	0.437 (0.501)	0.194 (1.416)	1.028 (1.222)	0.251 (1.252)
R&D expenditure	0.322*** (0.072)	-0.0566*** (0.010)	0.712*** (0.048)	0.623*** (0.097)	-0.373 (0.404)	0.260 (0.262)	2.570*** (0.723)
Coupling	-0.031 (0.182)	-0.026 (0.046)	0.339 (0.291)	0.796** (0.340)	0.188 (0.963)	-0.115 (0.921)	-5.280** (2.469)
Number of technological classes	-1.056*** (0.174)	-0.259*** (0.051)	-0.512 (0.353)	-0.688* (0.368)	-0.388 (1.888)	-1.120 (1.781)	0.307 (2.845)
Year	-0.0539*** (0.004)	-0.00279** (0.001)	-0.149*** (0.007)	-0.133*** (0.010)	-0.133*** (0.025)	-0.156*** (0.021)	-0.218*** (0.024)
Constant	109.2*** (8.611)	6.369** (2.624)	294.3*** (13.940)	261.3*** (20.520)	267.6*** (48.690)	310.0*** (40.190)	427.0*** (43.020)
Observations	1,395	1,395	1,395	1,067	173	212	112
Number of nuts3	93	93	93	80	21	25	9
Wald Chi2	522.400	134.100	743.900	214.700	69.910	117.400	307.200
LL	-3568.000	414.300	-4005.000	-2673.000	-557.200	-721.800	-466.200

All independent variables are in logarithm.

All independent variables are lagged one year.

Standard errors in parentheses

\*\*\* Significant at 1%

\*\* Significant at 5%

\* Significant at 10%

Table 3. 5: Determinants of explorative inventive performance

## **Discussion and conclusion**

The underlying idea of this study is that, in addition to technological knowledge expertise, regional alignment significantly affects its inventive performance and is a source of heterogeneity across the region. By considering regional alignment as the platform that characterizes the resource configurations of the region, we extend the literature that emphasizes the vital role of regional knowledge platform for its competitive advantage (Asheim et al., 2011; Boschma, 2004; Harmaakorpi, 2006; Harmaakorpi & Melkas, 2005). The results show that regional alignment has an impacts on regional innovative performances, both exploitative and explorative innovation. Our findings suggest that everything else being equal, “aligned” region (i.e. region with higher synergy potentials) provides local inventors with better opportunities and higher learning capacities for justifying different potential trajectories in the region. However, the levels of effect also vary across regions wiht respect to their R&D expenditure.

This paper contributes to regional development literature. The existing studies emphasize the critical role of regional knowledge bases in accelerating knowledge spillovers across local actors in the region. Such knowledge diffusion enhances regional innovation. Theoretical papers devote their attention to regional scientific and technological knowledge bases, which are complementary and configured to generate the synergy effects (Asheim et al., 2011; Asheim & Coenen, 2005; Asheim & Gertler, 2005). However, the relational properties between technological and scientific knowledge bases are not tested. Within the framework of the regional innovation system, regional alignment acts as a knowledge platform. On the one hand, it facilitates local inventors to identify themselves on a distributed knowledge in the region. On the other hand, the regional platform facilitates and guides the direction of collective learning and interactions across local actors (Lazaric et al., 2008). Accordingly, regional competitive advantage generates interaction in resource configurations. Moreover, these

dynamic capabilities enable the region to reform its competitive resource configurations based on the history's path and opportunities emerging from techno-socio-economic development (Harmaakorpi, 2006). Consequently, regional alignment can help local inventors to exploit their current competencies and explore the potential configured resources in the region.

To our acknowledgement, this study is the first attempt to conceptually and empirically integrates both technological and scientific knowledge expertise to examining its impact on regional innovative performance. In order to conduct this study, it takes us years to collect and process datasets. Accordingly, our regional alignment's concept and measurement are carefully constructed and built. As a result, our contribution is quite robust in this sense.

Our results also contribute to the literature of innovation management in terms of linkages between science, technology and innovation. Prior works have shown the critical role of science in stimulating technological advances (Ahuja & Katila, 2004; Fleming & Sorenson, 2004; Narin et al., 1997). The question emerged is whether one can interpret citation linkage between science and technology as direct links (Meyer, 2000). By studying front pages of patents in the field of nanoscale technologies and interview of 10 case studies, Meyer's paper shows that science citation reveals an indirect link in the sense that citations are not connected to the invention's process or the origin of whatever is patented. Instead, citations tell whether an invention touches a technological field that has not been patented before, and where the scientist has published something relevant (Meyer, 2000). It should be studied in the multifaceted interplay between science and technology. Our concept of regional alignment is appropriate to that sense. More specifically, regional alignment as a platform can be understood at two facets. On the one hand, it addresses a knowledge platform, which comprises of technological and knowledge expertise in the region. On the other hand, the platform implies

regional configurations between science and technology, which is not a linear one-way connection.

From a research perspective, this paper may be extended to other search topics. For instance, one can ask how network linkages between scientific and technological knowledge expertise may affect regional branching. We can assume that each technological field and scientific domain, which present in the region, are nodes and the density links between them are edges. The regional network is considered a small network in the national network. The high clustering and short average distance path across the node present the balance of the small-world network on a larger network (Kali, Reyes, McGee, & Shirrell, 2013).

While the effects of regional alignment across groups of regions with different amounts of R&D expenditure, the impacts of R&D are not consistent (both hypotheses). One may further focus on a specific group of regions having equivalent R&D expenditure to examine the effects of regional alignment on a set of technological industries, especially the groups of regions above the mean. In addition, the group of top-tier R&D investment regions benefits differently from R&D investments in terms of exploitative and explorative innovation. A future study may test the effect of regional alignment on the value of exploitative and explorative patents in a particular technological domain. These interesting research questions may unpack the black box to understand the process of knowledge creation of local inventors.

In the policy perspective, this paper stresses the path dependence of a regional platform. Beyond that traditional idea, it shows the role of alignment of the region, which comprises of technological and scientific knowledge bases associated with institutional supports to generate the synergy effects of configurations. Therefore, it brings benefits to local actors and creates heterogeneity in regional competitive advantage. In addition, the study suggests that regions benefit differently from regional alignment. More interestingly, the findings suggest that the

less advanced regions may profit from regional alignment for both exploitative and explorative innovation. As a consequence, the study promotes a “one size does not fit all” argument and calls for better place-based policy.

## **Conclusion**

This dissertation is inspired by the broad question that scholars in the geography of innovation try to answer. It is what are the underlying antecedents that create path development of regions. In this dissertation, I pay attention to the individual level to examine how the regional-specific context local affects the process of innovation creation. More specifically, I split this question into more focused questions. First, I attempt to understand the nature of knowledge input for innovation by proposing the fine-grained measurements for knowledge expertise of regions. Then I ask whether there is the connectedness of R&D expenditure and knowledge expertise of regions. Answering this question motivated me to other questions, such as “how the regional scientific expertise affects the development of regional innovation capacities by realizing and acquiring scientific knowledge faster”. Finally, we elaborate on the regional knowledge platform and to test whether it affects innovative capacities of local inventors. Each chapter in the dissertation answers each question. In this concluding section, I first review the answers provided by each chapter. Then, I spell out the main contributions that the dissertation makes. I also explain some of the limitations. Finally, I suggest some potential avenues for future work.

### **Answers to the research questions**

The first chapter is designed to exam the fundamental question of whether there is the connectedness between R&D expenditure and different types of knowledge expertise of regions. In this chapter, I address some of the limitations of the prior studies about the measurement of regional knowledge bases. The measurement fails to observe the dynamic knowledge elements and their interdependent relationships that underline the process of knowledge creation. The results show that R&D expenditure has the connectedness with the numbers of the scientific and technological expertise of the region. However, the level of

expertise is not connected to the level of R&D expenditure. I also show that the level of technological expertise will increase if it is complementary to a specific science. This finding verifies the important role of R&D investment. This chapter also shows that knowledge expertise is a promising unit of analysis to understand the process of knowledge generation.

The second chapter further answers the question related to the effect of regional scientific expertise on regional innovation capacities. In this study, we particularly examine the underlying mechanism for the diffusion of knowledge between science, innovation and technological progress. This chapter moves beyond the previous studies that only focus on knowledge diffusion across innovations. Here we highlight the importance of regional science and their relatedness to the local industry. We answer the research question by showing that the local scientific expertise, which is relevant to the focal technological innovation, decreases the time for local inventors reference to scientific knowledge. Moreover, we also show that the patents that cite the relevant science earlier have a higher impact on future technological patents. As a result, the findings are consistent with the idea that scientific expertise accelerates the diffusion of information between science and technology as well as between technologies.

The third chapter strives to answer the question about how regional alignment affects the innovative performance of regions. In this chapter, we propose the concept of regional alignment that draws from on the notion of a regional platform. We argue that regional alignment as a platform of knowledge systems generates a set of synergies between complementary and heterogeneous knowledge expertise and competence. These synergies facilitate interactive learning, thus increase absorptive capacities to local actors. When local inventors search for new knowledge elements, they may use these potential sources of knowledge. By screening and/or adopting the available knowledge, inventors may minimize risk and uncertainty. Moreover, it also enhances its innovative capacities. Our analysis suggests

that regional alignment increase the innovative performance of regions. In addition, it also enhances the explorative capabilities of regions by increasing the number of explorative patents. Further, in comparison with exploitative patents, the number of explorative patents is a decrease in explorative rate. This finding implies that local actors carefully evaluate and select the invention projects related to distant knowledge. Finally, the results also show that regional alignment helps to increase the usefulness of explorative innovations to future technologies.

## **Main contributions**

### *Contributions to the literature of geography innovation*

The dissertation sheds light on the underlying mechanisms of geography innovation. While the separate two streams of research increasingly become powerful concepts to explain the regional diversification, they still reveal some of the shortcomings. On the one hand, the differentiated knowledge bases emphasize the importance of knowledge subsystems of regions (Asheim and Coenen 2005; Asheim and Gertler 2006; Martin 2012). Under the regional specific context, there are interconnected between these systems that accelerate knowledge spillovers across local actors in the region. Such knowledge diffusion generates learning activities disciplines (Asheim et al. 2011; Manniche 2012; Strambach and Klement 2012). However, this line of research does not take into consideration the time as a critical dimension in the process of knowledge development (Manniche et al. 2017). As a result, the knowledge base taxonomies could not capture the characteristic of knowledge dynamics and the variation of knowledge bases. My dissertation takes into consideration by splitting regional knowledge bases into the fine-grained levels, which are knowledge expertise of regions. We further analyze the different types of expertise along the time and spatial dimensions. Therefore, we can gain a better understanding of the dynamics of local knowledge over time. Our results, particularly by the first chapter, show that the regional knowledge expertise differs across types and domains. They

also have a connectedness to R&D investment. Addition, the interdependence between science and local industry has a positive relationship with regional technological expertise.

On the other hand, the argument of technological relatedness is considered as a mechanism for knowledge diffusion between related sectors. It, thus, helps to explain regional growth as well as diversification (Boschma 2017; Boschma, Balland, and Kogler 2015; Frenken and Boschma 2007; Frenken et al. 2007). However, the relatedness largely ignores the role of unrelated knowledge in the processes of innovation creation (Grillitsch et al. 2018). Furthermore, the concept of relatedness is theoretically and empirically investigated across industrial sectors rather than between science and technology. As a result, this line of research largely ignores the knowledge sources from non-local space (Trippel et al. 2018). My dissertation overcomes this limitation by arguing that the relationship (interdependence) between science and technology also implies the relatedness. This relationship can be scaled from unrelated (independent) to related (dependent). Therefore, we can observe their interdependence either local (regional) and/or non-local (national, international) level. Besides, we also track these linkages along the time dimension. The results, all three chapters, support our ideas. Particularly, the first chapter shows that the level of the technological expertise of regions increases if it is relevant to a specific science.

The results of the second chapter suggest that the scientific expertise of regions, which is relevant to the focal technology, reduces the time for local inventor reference to scientific knowledge. Furthermore, it also helps to increase the use of the focal invention on future technology. The chapter broadens the literature of knowledge diffusion that the mechanism of diffusion not only happen between technology generations (patent-to-patents) but also between science-technology (scientific publications-to-patent). These findings are essential,

not only because science is generally assumed to be a source for innovation, but also because it helps to understand the process of referencing or of identifying useful scientific publications.

The third chapter extends the notion of the regional platform by conditioning the relatedness and both scientific and technological expertise of regions together. We argue the concept of regional alignment that the region has a high level of expertise on the set of technology and science, and those are related. Then, local inventors can benefit from that. It is a potential source for emerging new technology in the region. More than the benefits of relatedness, this chapter shows that the dynamic relationship between each pair of science and technology can mitigate the risk and cost in the search process. Moreover, these dynamic capabilities enable the region to reform its competitive resource configurations based on the history's path and opportunities emerging from techno-socio-economic development (Harmaakorpi, 2006). Consequently, regional alignment can help local inventors to exploit their current competencies and explore the potential configured resources in the region.

In sum, my dissertation contributes to the current academic debate on how regions generate new industrial development and economic growth. For example, the policy of smart specialization is to focus on the structural transformations of a limited number of well-identified domains to facilitate entrepreneurial discovery processes and generate intra- and inter-sectoral spillovers (Foray 2018; Foray, David, and Hall 2011; McCann and Ortega-Argilés 2015). Smart specialization policy concept promotes the idea that the realization of regional innovation and economic potentials relies on the ability to develop a unique et superior knowledge base. The identification of those priority domains is challenging and requires significant statistical capacities to estimate the comparative advantages of the region. As we showed, in particular, the interdependence between technological and scientific knowledge expertise (or regional

alignment) are critical sources for industrial development and structure change of regions because it affects both the exploitative and explorative innovation performance.

*Contributions to the literature of search process model for innovation*

This dissertation also contributes to the literature of innovation management in terms of linkages between science, technology and innovation. Prior works have shown the critical role of science in stimulating technological advances (Ahuja and Katila 2004; Fleming and Sorenson 2004; Gittelman 2016; Gittelman and Kogut 2003; Narin et al. 1997; Nelson 1959; Sorenson and Fleming 2004). However, Meyer (2000) questions whether the citation linkages between science (scientific publications) and technology (patents) can be interpreted as the diffusion of knowledge. Meyer's results show that science citation reveals an indirect link in the sense that citations are not connected to the invention's process or the origin of whatever is patented. Instead, citations tell whether an invention touches a technological field that has not been patented before, and where the scientist has published something relevant (Meyer, 2000). He suggests the patent-publication citation implies the multifaceted interplay between science and technology. Indeed, scientific research is a complex and multifaceted activity, which is time-dependent and context-dependent (Tijssen 2010). The concept of regional alignment, in the third chapter, is appropriate to that sense. More specifically, regional alignment as a platform can be understood at two facets. On the one hand, it addresses a knowledge platform, which comprises of technological and knowledge expertise in the region. On the other hand, the platform implies regional configurations between science and technology, which is not a linear one-way connection.

Further, the results of the dissertation reveal the source of knowledge underlying the processes of innovation generation. Even though, the searching for sources of knowledge are well-documented in previous (Afuah and Tucci 2012; Ahuja and Katila 2004; Breschi and

Catalini 2010; von Hippel 1994; Jaffe et al. 1993; Phene, Fladmoe-Lindquist, and Marsh 2006; Sorenson and Singh 2007; Stuart and Podolny 2007), the mechanism behind the search's behaviour of local inventor is not extensively investigated, except the recent study of Bikard and Marx (2018). Their study is more focused on the role of technology of regions as a hub to link science and industrial technology. My dissertation, however, emphasizes the importance of all types of knowledge expertise of regions. In particular, we highlight not only the regional technological expertise but also scientific expertise and the relatedness between them. We believe that the synergy between science and local technology is a critical factor that makes the value of innovation differently.

#### *Methodological contributions*

Most studies underlying the concept of differentiated of knowledge bases of region use data on employees' occupations to measure firm or regional knowledge bases (Asheim et al. 2011; Asheim and Hansen 2009; Blažek and Kadlec 2019; Grillitsch et al. 2017; Květoň and Kadlec 2018; Martin 2012). However, as we claimed, the method overlooks the possible discrepancy between main activities registered in the occupation classification and the actual activities carried out in the firm, and it also ignores the time dimension in the process of knowledge creation (Manniche et al. 2017). My dissertation overcomes these shortcomings by collecting the datasets of both patents and publications over 25 years. To our acknowledgement, this dissertation is the first attempt to conceptually and empirically integrates both technological and scientific knowledge expertise to examining its impact on innovative performance of regions. In order to conduct this study, it takes us years to collect, clean and process datasets. Accordingly, our measurements of regional knowledge expertise, their interdependence and the alignment are carefully constructed and built. As a result, our contribution is quite robust in this sense.

Moreover, the datasets at the individual level of a patent and a scientific publication set us as the point of view of inventors and/or scientists. Using their affiliated address rather than the applicant's address (usually the headquarters) help us to identify the location of inventors. One can assume that the location is where the processes of knowledge generation occur. Hence, we can observe the localized agglomeration effects. Moreover, the sample of all French regions over a long period helps us to lead us to consider the heterogeneity problems of regional specific fixed-effects and year fixed-effects that may affect our dependent variables.

Furthermore, knowing inventor-given references sets us apart from the prior studies that primarily focus on analyzing the scientific publications given by patent examiners but not on the references of patent inventors (van Vianen et al. 1990). Additionally, the datasets are to track the patent-publication citations in France in 25 years that prevent us from the heterogeneity problems of inventor preferences on scientific publications (such as the language barrier). At least, these publication-patent citations are tested under the same national context.

The third chapter also contributes to the measurement of technological trajectory. Indeed, a search process also indicates that new knowledge can be referenced through the direct and indirect source. State differently, the value of the focal patent can be measured by the use of not only the future direct citing innovation but also the indirect citing innovations. The impact of the focal innovation on technological progress is captured by the direct count of forward citation and the multi-generational forward citation tree. While most previous studies use the forward citations count to measure the *impact* of the cited patent to the directly citing patents, this method may not observe the explicit influence of a patent on future technologies. The exceptional works of Corredoira and Banerjee (2015) and Corredoira et al. (2018) suggest to observing not only the direct citing patents but also the indirect ones. These authors argue that the multi-generational forward citation tree captures the *influence* of the focal patent to

technological trajectory over the long term because this measurement counts both the direct and indirect forward citations of the focal patent. In this chapter, this measurement allows us to observe the impact of the diffusion of knowledge on the overall technological progress.

In addition, the ten-year window of forward citation count allows us to capture the heterogeneity on the time lag of publication-patent citations in different technologies. More specifically, the most common measurement of the *impact* of the patent is to count the number of prior art citations that the patent received during the first five years since it was granted (Dibiaggio et al. 2014; Fleming and Sorenson 2004). This five-year window of forward citation count is a short time, which could not measure the *impact* of the patent in some technologies. For example, Fukuzawa and Ida (2015) find that the life and medical technology group takes six-to-eight years for the peak citation of the patent. It also takes eight-to-ten years for the time lag of patent-patent citations in biofuels, solar and wind technology group (Popp 2017). As a result, our ten-year window count of forward citation is enough long-period for a patent to be recognized and cited by other patents, which may capture the differences in the diffusion of knowledge across technologies.

#### *Contributions to the management and policy*

My dissertation disentangles the processes of knowledge generation underlying for innovation. It can be applied to deliver appropriate strategies and policies, which are relevant to the linkage between science, innovation and technological progress, at different levels: inventor-, firm-, industry-, regional-, and national levels. In particular, at the individual levels of inventor and firm, they may have an overall map of the external sources of knowledge that are closely related to their focal technological projects. As a result, it may guide them on how to search and acquire new knowledge.

For industrial and regional level, the diffusion of knowledge of science to technology (the relatedness) may help industrial sectors to rejuvenate its innovation advantage by acquiring potentially scientific knowledge and identifying the specific time for their acquisition. Consequently, the outcomes of the patenting activities may accelerate future technologies. Finally, from the R&D policy' perspective at the national level, understanding the underlying mechanism to reference scientific publications of inventors may help policymakers to navigate their policies which regions and scientific domains are useful to local firms. Therefore, they may navigate and accelerate the specific investment for science.

### **Limitations**

This dissertation is subject to several shortcomings. First, we acknowledge that the process of knowledge creation is complex and hard to be observed by a set of patents and publications. Even though our datasets allow to conceptualize the individual and community (regional) level of knowledge underlying the innovation generation, we can not take into account the organizational level. Indeed, the organization-managerial level is critical processes that involve organization decision-makers (Manniche et al. 2017). In particular, these processes relate to recognizing the demand for innovation, to allocate the resources and team for the project, to coordinate internal and/or external knowledge sources. However, the dissertation aims to provide an overview of various types of knowledge expertise and their dynamic relationships.

Besides, at the individual level (inventors, scientists), my dissertation may not explicitly capture the insights of inventors behind their search processes. As Meyer (2000) mentioned, the sources of knowledge can stem from the general and/or teaching experience. Even though our large datasets can not capture this factor, they provide us with a general review of the search model of inventors in French regions.

In my dissertation, because localized interactive learning is a vital mechanism for innovative activities, the institutional factor should be taken into account. Indeed, Asheim et al. (2011) argue that the regional institutions are laid down in the past, which may affect the innovation potential of regions. First, regional policy is usually in a state of competition to attract skill-labours and capital investments (Florida, 2002). Second, regions cannot take direct actions to mitigate the poor performances of local firms. However, regions can play active roles in terms of expressing regional interests such as the strategic goals of enhancing their competitive advantages on a particular set of technologies and/or sciences. The regional strategies may generate more opportunities and/or constraint local inventors/firms' search behaviours (e.g. due to their economic history or advantage location) (Boschma, 2004). However, our datasets and theoretical frameworks are constructed based on the detailed information of local inventors and scientists (e.g. patents and scientific publications), they explicitly reflect the process of interactive learning and generation in the region.

### **Motivating new research**

My dissertation unbundles the black box of the processes of knowledge generation in the regional specific context. It also opens a promising research avenue in different directions. First, regarding the first chapter, we suggest to extend and move the scheme of research agenda towards more advanced works relying on regional knowledge expertise. For instance, one can extend our results by using the USPTO data to construct regional knowledge expertise. Then the research question is whether a region combining the high level of relatedness of a specific pair of science and technology is more innovative than those regions combining both high and low levels of relatedness across science and technology.

Regarding the research stream of the network, one can ask how network linkages between scientific and technological knowledge expertise may affect regional branching. We

can assume that each technological field and scientific domain, which present in the region, are nodes and the density links between them are edges. The regional network is considered a small network in the national network. The high clustering and short average distance path across the node present the balance of the small-world network on a larger network (Kali, Reyes, McGee, & Shirrell, 2013).

At the microlevel, one may examine whether levels of dependence between specific pair science and technology enhance the inventiveness of innovation (in terms of explorative and exploitative). One can assume that an innovation, which combines the high relatedness of technology to the focal innovation and the low relatedness to a specific science field, may create a potential combination. This low relatedness to a specific science implies potentially unexplored combination rather than an unfruitful combination. Therefore, inventors may project their combination search, which helps to reduce risks and costs.

In addition, the one may ask whether a granted scientific publication may receive a faster citation from patent and whether it increases the value of the focal patent. Furthermore, whether the publication in applied research receives more citations than basic publications. Answering these questions may help policymakers to adjust and allocate the grants.

Regarding the third chapter, one may ask whether regional alignment can leverage the distant knowledge sources (either a specific science and/or technology) for less-developed regions. This strategy may help them to explore the potential market that is at the early stage. Or they still exploit their neighbour knowledge expertise to catch up.

Last but not least, the effects of R&D on the innovative performance of regions are not consistent across technological industry groups in the third chapter. One may limit the sample

on regions having equivalent R&D expenditure and the same technological groups to examine the effects of regional alignment on innovation in terms of exploitative and explorative patents.

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## Appendix 1

	<b>Technology</b>		<b>Science</b>
1	Electrical machinery, apparatus, energy	1	Agriculture, Fisheries & Forestry
2	Audio-visual technology	2	Biology
3	Telecommunications	3	Biomedical Research
4	Digital communication	4	Built Environment & Design
5	Basic communication processes	5	Chemistry
6	Computer technology	6	Clinical Medicine
7	IT methods for management	7	Communication & Textual Studies
8	Semiconductors	8	Earth & Environmental Sciences
9	Optics	9	Economics & Business
10	Measurement	10	Enabling & Strategic Technologies
11	Analysis of biological materials	11	Engineering
12	Control	12	General Arts, Humanities and Social Sciences
13	Medical technology	13	General Science & Technology
14	Organic fine chemistry	14	Historical Studies
15	Biotechnology	15	Information & Communication Technologies
16	Pharmaceuticals	16	Mathematics & Statistics
17	Macromolecular chemistry, polymers	17	Philosophy & Theology
18	Food chemistry	18	Physics & Astronomy
19	Basic materials chemistry	19	Psychology & Cognitive Sciences
20	Materials, metallurgy	20	Public Health & Health Services
21	Surface technology, coating	21	Social Sciences
22	Micro-structural and nano-technology	22	Visual & Performing Arts
23	Chemical engineering		
24	Environmental technology		
25	Handling		
26	Machine tools		
27	Engines, pumps, turbines		
28	Textile and paper machines		
29	Other special machines		
30	Thermal processes and apparatus		
31	Mechanical elements		
32	Transport		
33	Furniture, games		
34	Other consumer goods		
35	Civil engineering		