R&D and Knowledge Expertise of French Regions

Tan Tran
R&D and Knowledge Expertise of French Regions

Tan TRAN
SKEMA Business School, Sophia Antipolis, France
Université Côte d’Azur
Jan, 2020

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 suggesting to measure 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
1. 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, Boschma, and Cooke 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, Coenen, and Asheim 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, Martin, and Srholec 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, Moodysson, and Testa 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, Hamilton, and Olivastro 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; Květoň 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 Tripple (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 (Blazek 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\(^1\). Our data of publication-patent citations help us to track up these

---

\(^1\) The relationship between science (publications) and technology (patents) is extensively discussed in recent works (Gallaert, 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 2000a; van Vianen et al. 1990). In this chapter, we only observe the
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.

Therefore, the objective of the study is to observe the types of knowledge expertise, particularly scientific and technological expertise\(^2\), in the RISs. Second, we investigate the connectedness of R&D expenditure\(^3\) 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 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.

---

\(^2\) 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.

\(^3\) 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.

2. 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 2000a; Narin et al. 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. 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 specializes 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.

3. Methodology for measuring knowledge expertise

3.1 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\textsuperscript{4}. 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 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

\footnote{4. Further details, please refer to Archambault, et al., 2011 and Gomez et al., 1996}
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.

3.2 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).
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\(^5\) 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)\(^6\). 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.

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.

\(^5\) Authors affiliated to a French university, public or private research institution or corporation.

\(^6\) See Appendix 1
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 2000b; 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 3: The trend of scientific citations per patent in France (1990-2015)

3.3 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:

$$P_{jt} = \sum_{t-4}^{t-1} P_{jt-1}$$

where $t = \{1990, \ldots, t, \ldots, 2013\}$  \hspace{1cm} (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 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

$$RTE_{r} = \frac{\sum_{i} p_{ir}}{\sum_{i} \sum_{r} p_{r} / \sum_{i} \sum_{N} p_{N}}$$

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; $p_{N}$ 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

$$RSE_{jr} = \frac{\sum_{j} p_{jr}}{\sum_{j} \sum_{r} p_{r} / \sum_{j} \sum_{N} p_{N}}$$

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.
\[
\lambda_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}}, \quad \lambda_{ij} \in R
\]

(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.

\[
\lambda'_{ij} = \frac{\lambda_{ij} - \text{Min}\lambda_{ij}}{\text{Max}\lambda_{ij} - \text{Min}\lambda_{ij}}
\]

(4)

4. 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.

4.1 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

---

7 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 expertise⁸, 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).

---

⁸ The other study applies a different threshold value of location quotient (LQ) as a sign of strong regional specialization (Martin 2012).
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 level (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.
Figure 5(a, b, c): The average of regional scientific expertise of regions (2000-2007)
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).
Figure 6a, 6b, 6c: 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.

4.2 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.
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.
Technological index of regions with high R&D expenditure (2000-2007)

Technological expertise index

Numbers of technological field having expertise index greater than one

- Haute-Garonne (FR623)
- Seine-et-Marne (FR102)
- Val-d'Oise (FR108)
- Rhône (FR716)
- Yvelines (FR103)
- Seine-Saint-Denis (FR106)
- Essonne (FR104)
- Hauts-de-Seine (FR105)
- Paris (FR101)
- Val-de-Marne (FR107)

Seine-Saint-Denis (FR106)
Figure 8a, 8b, 8c: 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.
Figure 9a, 9b, 9c: The scientific expertise of regions in 2000
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 the same 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 sixteen 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.

4.3 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\(^9\). 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 (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

---

\(^9\) Only the relationship between nodes having more than 100 linkages are displayed.
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 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 Trippl 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.
5. 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 combing 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.
## Appendix 1

### Table 1: List of Technology and Science

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


