

How smart is specialisation? An analysis of specialisation patterns in knowledge production

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Abstract

To understand how the specialisation patterns of cities differ among scientific fields, we study patterns of knowledge production in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry in the period 1996–2012. Using keywords from journal publications, we find systematic differences across scientific fields, but remarkable similarities across cities within each field. Biotechnology shows a turbulent pattern with comparative advantages that are short lasting, and with few related topics available for research locations. Astrophysics—and in later years Nanotechnology—show a pattern of stable rankings, comparative advantages that last longer, and many related topics potentially available for research locations. Organic Chemistry has an intermediate position. Thus, fields of knowledge production have fundamentally different characteristics that require different smart specialisation strategies taking into account the differences in accumulation and relatedness.

Key words: smart specialisation; scientific knowledge dynamics; path dependency; innovation policy.

1. Introduction

Smart specialisation—an innovation policy concept intended to promote the efficient and effective use of public investment in research—was an instant hit with European policy-makers. Its goal is to boost regional innovation in order to achieve economic growth and prosperity, by enabling regions and cities to focus on their strengths (Foray et al. 2009). Smart specialisation means identifying the unique characteristics and assets of each region, highlighting each region's competitive advantages, and rallying regional stakeholders and resources around an excellence-driven vision of their future (McCann and Ortega-Argilés 2013).

It can be difficult for policy-makers to decide how widely to spread their limited investments across the range of leading-edge science and technology, especially in regions that are not at the forefront of any specific fields. The notion that cities and regions should specialise seems intuitive. Regions cannot be good at everything; they must concentrate on what they are best at—on their comparative advantage. Knowledge production is very unevenly distributed over regions (Florida 2005), and many regions struggle to replicate the levels of productivity and innovativeness achieved in leading regions. The key to this struggle is the building up of an institutional context that facilitates the production and exchange of knowledge (Asheim et al. 2006).

The question is whether there is a 'smart specialisation' alternative to policies that spreads investments thinly across many research

topics, and, as a consequence, do not make much of an impact in any one area (Todtling and Trippl 2005). A more promising strategy appears to be to encourage investment in programmes that will complement existing skills and infrastructures to create future capability and comparative advantage (Hausmann and Hidalgo 2009).

Indeed, cities and regions do specialise. The cumulative and path-dependent character of knowledge production also makes it place-dependent (Heimeriks and Boschma 2014). This implies that locations for research are likely to specialise over time. At the same time, knowledge production is also subject to dynamics: new topics emerge, and new research locations come to prominence. These different specialisation patterns contribute to the rise and fall of research locations.

While there are many studies to show that regional specialisation occurs (Boschma 2004; Boschma et al. 2014), there are few that address the question of how 'smart' this specialisation is, and whether the specific type of research activity undertaken actually matters? Yet these questions are vital if we are to make sensible policies towards innovation-driven economic development.

In this study, we explore the regional specialisation patterns of scientific knowledge production in different fields over a period of time. From an evolutionary perspective, we argue that the cumulative and path-dependent nature of scientific knowledge production also makes it place-dependent. This implies that research locations

are likely to specialise over time (Heimeriks and Boschma 2014). At the same time, knowledge production is also subject to dynamics: new scientific topics emerge, and new research locations come into existence across the globe (Heimeriks and Boschma 2014). The aim of this paper is to quantify these evolutionary patterns of knowledge production in different fields and to show how these different path- and place-dependent specialisation patterns contribute to the rise and fall of research locations. We use the body of codified knowledge accumulated in scientific publications during the period 1996–2012 as data for our analysis. Key topics are used as an indication of cognitive developments within the scientific fields over a period of time.

It can be expected that different fields of knowledge production provide very different opportunities for (smart) specialisation. Different fields rely on local skills, tacit knowledge and infrastructures to varying degrees (Heimeriks 2012) and differ in the extent to which the codified body of knowledge is accumulative (Bonaccorsi 2008). Furthermore, different fields of knowledge can be expected to differ in the way in which they provide opportunities for locations to contribute (Heimeriks and Boschma 2014), related to the differences in task uncertainty and mutual dependence among researchers in each field (Whitley 2000).

The remainder of this paper is structured as follows: in Section 2, we set out theoretically why we expect that scientific knowledge production is characterised by a path- and place-dependent process of specialisation. Section 3 introduces the data and methodology. Section 4 investigates the rise and fall of research locations in relation to scientific topics as proxied by keywords. In Section 5, we assess the extent to which the emergence of new scientific topics at different locations is dependent on their degree of relatedness with existing topics present at those locations. In Section 6, we discuss the results and derive policy implications and Section 7 draws conclusions.

2. The evolution of knowledge

It has long been recognised that the accumulation of knowledge is central to economic performance (Nelson and Winter 1982; Romer 1994; Schumpeter 1943). In recent years, the importance of knowledge production has further increased because of economic globalisation, and the ease of transmitting codified information across geographical space through the internet, scientific journals, international conferences and mobility of scientists (David and Foray 2002; Heimeriks and Vasileiadou 2008). The term 'knowledge-based economy' stems from this fuller recognition of the place of codified knowledge¹ in modern societies (OECD 1996). Perhaps the single most important characteristic of recent economic growth has been the rising reliance upon codified knowledge as a basis for the organisation and conduct of economic activities. Affecting individual and organisational competencies and the localisation of scientific and technological advances, codification has been both the motive force and the favoured form taken by the expansion of the knowledge base (Foray 2004).

Many studies of science and innovation have drawn inspiration from evolutionary economics and mechanisms of path-dependence (Nelson and Winter 1982). In this study, we use the two main strands of the evolutionary literature, namely knowledge-related path-dependence and location-related place-dependence, the two main 'carriers of history' as David (1994) calls them, as the building blocks of an evolutionary approach to knowledge dynamics. These evolutionary dependencies in knowledge and locations are clearly

related. Particular locations are characterised by particular knowledge developments which build on existing knowledge for further knowledge production (Arthur 1994).

From this perspective, different phenomena can be put forward with respect to the nature of knowledge developments. The first is that from an evolutionary perspective, existing scientific knowledge provides building blocks for further knowledge production. New knowledge evolves from the chaotic and constant recombining of already existing knowledge building blocks (Arthur 2007). Kauffman coined the name for the set of all possible new knowledge combinations: 'the adjacent possible'. The phrase captures both the limits and the potential of change and innovation in knowledge developments (Kauffman 1993). The path-dependent evolution of knowledge involves the dissemination of results through scientific journals which translates the 'research output' produced by research locations into an emergent 'body of knowledge' where codified claims are utilised (accepted, criticised, and rejected) by others. Thus, science is a global, collective and distributed system in which researchers are positioned with respect to the global knowledge base (Fujigaki 1998). Thus, this global body of scientific codified knowledge acts as a focusing device for the whole scientific community (Boschma et al. 2014).

Second, knowledge is differentiated among locations, given that it is specific to the context in which it is created. The importance of spatial proximity in lowering the barriers and costs of knowledge sharing and transmission is related to the basic properties of knowledge and learning processes, most of all their degree of complexity and tacitness (Breschi et al. 2003). Due to its partly tacit nature, knowledge has unique and characteristic features in each new learning environment. Furthermore, knowledge developments are partially irreversible: once new topics and the accompanying skills and routines have moved on, previous or simpler topics are 'forgotten', and to reintroduce them would require a new learning process and the modification of individual and collective skills, organisational practices and institutions (Lundvall 1998). What constitutes success in the current knowledge economy for regions is rapid learning and forgetting, because old ways of doing things often get in the way of learning new ways in a process of creative destruction (Lorenz et al. 2007).

Moreover, new scientific topics emerge and important new locations of research also frequently appear in a globalising world. When locally embedded knowledge is combined in novel ways with codified and accessible external knowledge, new knowledge and ideas can be created (Heimeriks and Boschma 2014). Consequently, the creation of new knowledge is expected to be characterised by a path-dependent process of branching: new knowledge is developed from existing knowledge, skills and infrastructures in relation to global scientific developments.

All these phenomena can be expected to have crucial implications for the spatial dynamics of knowledge, and the associated rise and fall of research locations.

Our first hypothesis (Hypothesis 1) is that the cumulative and path-dependent nature of scientific knowledge production is likely to contribute to the concentration of scientific activity in which locations specialise within particular scientific topics. Thus, the topic repertoire of most locations is expected to only comprise a small subset of the range of recombinant possibilities that define knowledge space, and there are costs associated with search in that space (Heimeriks and Boschma 2014; Rigby 2015). These costs are related to the topography of knowledge space that Kauffman (1993) imagines as a fitness landscape where knowledge claims are

characterised by the number of components (topics) and the extent of the interaction between them. Each of these topics is associated with a level of fitness. The ease (cost) of search, within fitness landscapes is shown to depend on the extent of the interaction between the components that comprise particular topics.

We also expect that, as locations specialise in particular competences, these specialisations will offer opportunities for further improvements in similar topics, and discourage the creation of knowledge on topics unrelated to the local knowledge base (Boschma et al. 2014). The local accumulation of tacit knowledge provides an intangible asset that is difficult for non-local agents to cope with, as geographical distance may form an insurmountable barrier to the transfer of tacit knowledge. Thus, Hypothesis 2 is that the entry and exit of topics at different locations can be explained by their relatedness to the existing knowledge portfolio at each location. Related topics are more likely to enter the scientific portfolio of a city than unrelated topics.

However, different scientific fields can be expected to constrain and facilitate the local opportunities for researchers to different degrees. Antonelli (1999) suggests that knowledge production is the result of a complex process of the creation of new knowledge which builds not only upon formal research activities, but also on the mix of competences acquired by means of learning processes, the socialisation of experience, and the recombination of available information. Thus, knowledge production draws upon four different forms of knowledge: tacit and codified, and internal and external to each research organisation (Antonelli 1999). Different fields of knowledge rely on local skills, tacit knowledge and infrastructures to varying degrees and differ in the importance of learning processes, the socialisation of experience, and the recombination of available information (Heimeriks et al. 2008). Moreover, fields can be expected to differ in the extent to which the codified body of knowledge is accumulative or divergent (Bonaccorsi 2008). Fields of research also differ in the ‘context of application’, that is, the ease of appropriability of knowledge in socio-economic contexts which may guide the direction of search (Heimeriks and Leydesdorff 2012). There are obvious complementarities between science and innovation which, however:

... varies considerably amongst sectors of application, in terms of the direct usefulness of academic research results, and of the relative importance attached to such results and to training. (Pavitt 1987: 7)

Our third hypothesis is that different patterns of local specialisation exist over time among different scientific fields with distinct patterns of comparative advantages among research locations. A useful framework for understanding the different properties of knowledge and learning processes is provided by Whitley (2000) who argues that differences among scientific fields can be conceptualised along the dimensions of ‘task uncertainty’ and ‘mutual dependency’. ‘Task uncertainty’ concerns the unpredictability of task outcomes. Because the sciences are committed at an institutional level to produce novel results, research activities in all fields are fundamentally uncertain in that outcomes are not repetitive and predictable. However, scientific fields can be expected to differ in the extent to which task uncertainty plays a role. In fields of knowledge that are highly cumulative and have a shared agenda of important research topics, task uncertainty is relatively low.

‘Mutual dependence’ relates to the extent to which researchers are dependent upon knowledge produced by others in order to make a significant contribution (Whitley 2000). As a consequence, the

coordination of expensive infrastructures can be legitimised more easily for stable fields of knowledge production which have relatively low task uncertainty and high mutual dependency.

The creation of competitive advantage at the regional level has long focused attention on the ability of place-based agents to acquire relevant knowledge and on their capacity to use that knowledge effectively (Cohen and Levinthal 1989; Storper 2010). The knowledge bases of regions shift over time, but in different ways among different fields. From the point of view of knowledge production, each region is a repository of specialised knowledge that is positioned with respect to the evolving global body of knowledge. Where topics are associated with distinct geographical areas, lasting comparative advantages may emerge, reflecting place-specific sets of competences and capabilities (Boschma and Frenken 2009).

In analogy with Schumpeterian patterns of innovation, we hypothesise ‘Schumpeter Mark I’ and ‘Schumpeter Mark II’ types of knowledge development (Malerba and Orsenigo 1996). Fields that are characterised by low levels of mutual dependence and high levels of task uncertainty can be expected to exhibit a turbulent pattern of development, with different locations contributing to different topics (Hypothesis 3a).

In reverse, we hypothesise that fields characterised by high levels of mutual dependence and low levels of task uncertainty will exhibit strongly accumulative patterns of knowledge developments where different locations mutually contribute to the same range of topics. Consequently, the ranking is more stable and comparative advantages can be expected to last longer (Hypothesis 3b).

3. Data and context

It is generally accepted that the accumulation of knowledge is central to innovation and economic performance. In this paper we are not focusing directly on innovations (the application of new knowledge), but instead on the spatially distributed knowledge production and accumulation as made visible in scientific publications over time. Scientific communications are extremely well archived. We therefore have a wealth of data at our disposal.

Our methodology follows the ‘product space’ framework, which integrates network science with macroeconomic theories in order to understand the uneven development of countries (Hidalgo et al. 2007). This framework develops a two-mode network approach of the economy constructed from country-product pairs (Hidalgo et al. 2007). In this paper, we apply the product space framework to scientific knowledge dynamics, and our two-mode network is based on pairs of city-topics constructed from publication records in different fields in the period 1996–2012.

3.1 Data

Publication practices are heterogeneous within and between fields. The delineation of fields remains fuzzy. Nevertheless, in a study of aggregated journal–journal citations it was argued that one can track fields by defining ‘central tendency journals’ (Leydesdorff and Cozzens 1993). In this paper, we will use two ‘central tendency’ journals in each field to map the development of the fields of Biotechnology, Nanotechnology and Organic Chemistry in the period 1996–2012. Each pair of journals is selected as representative by its continuous presence in the core set of journals representing the field.²

All metadata from the publications in these fields as retrieved from the ISI Web of Science could be organised in a relational

database as the basis for the analysis. The data contains the addresses as identified by the ISI Web of Science. Thus, the database enables us to specify the number of publications and their topics (as indicated by keywords) of all locations over a period of time. As such, the data allows us to study the rise and fall of cities in co-evolution with the changing topics of research. Papers with multiple addresses were fully attributed to each location.

The use of keywords in the publications provides us with an indication of the cognitive developments within the field. In this paper the 'KeyWords Plus' are used as indicator of topics representing the cognitive development in the different fields. KeyWords Plus are index terms created by Thomson Reuters from significant, frequently occurring words in the titles of an article's cited references. Because this standardised index was used, no further stemming was applied to the keywords.

Several indicators based on keywords have been developed to trace the development of science (Leydesdorff 1989). These quantitative methods rely on measuring relations between different pieces of information, positioned in a network with an emerging (and continuously reconstructed) structure (Leydesdorff 2010). In this way, an evolving discourse of scientific topics can be measured by using keywords and their co-occurrences as the observable variation.

3.2 Context

The cases for our empirical operationalisation of evolving knowledge dynamics were selected as representative of patterns in global knowledge production in the sciences. The selection includes the emerging sciences Biotechnology and Nanotechnology as well as the more traditional fields of Astrophysics and Organic Chemistry that are included in the analysis for comparison (see Table 1).

Astrophysics is expected to be an example of a field that has high levels of 'mutual dependence', but low levels of 'task uncertainty', and represents a clear example of government supported 'big science'. Knowledge production requires massive and unique infrastructures such as observatories and satellites, which makes government funding inevitable (Price 1963). There is a continuous push for larger telescopes, or larger arrays of telescopes, to allow astronomers to see dimmer objects and at greater resolutions. Astrophysics is characterised by a high reliance on collaborative research, a cumulative tradition, substantial governmental funding, and an extensive use of data and physical infrastructures (Heimeriks et al. 2008).

Biotechnology is characterised by an interdisciplinary knowledge development with emphasis on applications, and a variety of producers and users of the knowledge (Heimeriks and Leydesdorff 2012). The combination of problem variety, instability, and multiple orderings of their importance with technical standardisation occurs especially in this field (Whitley 2000). Furthermore, as a relatively new

field, Biotechnology is characterised by rapid growth, divergent dynamics and new complementarities (Bonaccorsi 2008). The knowledge base has been characterised by turbulence, with some older topics becoming extinct or losing importance (related to food preservation and Organic Chemistry) and with some new ones emerging and becoming important components (related to molecular biology and physical measurements) (Krafft et al. 2011). The transition to genomics-based technologies led to a discontinuity in the pattern of knowledge production because the competencies required in the new practices differed as bioinformatics acquired a key role in the sequencing of genomes (Saviotti and Catherine 2008).

Like Biotechnology, Nanotechnology is an emerging technoscience characterised by high growth, high diversity, and large human capital and institutional complementarities that requires a very diverse instrument set (Bonaccorsi and Thoma 2007). Nanotechnology is highly interdisciplinary (Leydesdorff and Schank 2008) and is expected to have major economic and social impacts in the years ahead. Inventive activities in Nanotechnology have risen substantially since the end of the 1990s and funding has increased dramatically (OECD 2009). Mutual dependence is expected to be relatively high in this field because of the need for expensive infrastructures (e.g. clean rooms).

The knowledge development in Organic Chemistry is expected to be highly cumulative as an example of a field that has relatively low levels of 'mutual dependence' compared to Astrophysics, as well as low levels of 'task uncertainty' (Whitley 2000). Organic Chemistry is a long lasting field characterised by a low-to-medium growth, low diversity, and a low complementarity search regime. Furthermore, it is generally acknowledged that chemistry has been evolving around bilateral cooperation at national level between the universities, research institutes and firms (Bonaccorsi 2008).

In summary, the four fields can be expected to be positioned along the dimensions 'task uncertainty' and 'mutual dependence' (see Table 2). Fields characterised by low levels of mutual dependence and high levels of task uncertainty can be expected to exhibit a turbulent pattern of development. Fields characterised by high levels of mutual dependence and low levels of task uncertainty can be expected to exhibit very accumulative and stable patterns of knowledge developments.

3.3 Measuring scientific coherence

Analysing the level of average scientific coherence requires three main steps. Scientific coherence describes, on average, how similar (understood as scientifically related) are the topics in which a city is active. At the city level, it comes close to the concept of specialisation (see Kogler et al. (2013) in the context of technological knowledge), while aggregated at the field level it reveals patterns of path- and place-dependence in the process of knowledge dynamics (Kogler et al. 2013).

First, one needs to measure the scientific relatedness among keywords in a specific field. In this paper, we use a simple and

Table 1. Central tendency journals and number of articles per field

Field	Journal	Number of articles
Astrophysics	<i>Astrophysical Journal</i>	36572
	<i>Astronomy and Astrophysics</i>	28531
Biotechnology	<i>Biotechnology and Bioengineering</i>	5873
	<i>Journal of Biotechnology</i>	3508
Nanotechnology	<i>Nanotechnology</i>	7494
	<i>Nano Letters</i>	9421
Organic Chemistry	<i>Journal of Organic Chemistry</i>	23848
	<i>Organic Letters</i>	18420

Table 2. Position of different fields along dimensions 'task uncertainty' and 'mutual dependence'

		Mutual dependence	
		High	Low
Task uncertainty	High	Nanotechnology	Biotechnology
	Low	Astrophysics	Organic Chemistry

normalised measure of relatedness based on the co-occurrences of keywords within journal articles. We use the Jaccard index to account for the number of occurrences of each keyword. With occ_{ij} denoting the total number of times that i and j co-occur in the same journal article, and occ_i denoting the total number of occurrences of i , the relatedness $\phi_{i,j,t}$ between each topic i and j is given by:

$$\phi_{i,j} = \frac{occ_{ij}}{occ_i + occ_j - occ_{ij}} \quad (1)$$

As a result, the measure is symmetric and $\phi_{i,j,t} \in [0, 1]$. A value of 0 indicates that the two topics never co-occurred within the same journal article, while a value of 1 indicates that the two topics systematically co-occur.

In a second step, we create a city–topic level variable *relatedness density* that combines the information given by the relatedness $\phi_{i,j,t}$ between topics with the scientific activity of cities (i.e. the set of topics on which they publish (see Boschma et al. 2014 for a more technical description)). This variable will be our main variable of interest in the econometric analyses and it indicates how close a topic is to the existing scientific portfolio of a given city. The spatial allocation of topics to cities is constructed from the addresses mentioned in journal articles. As a result, the relatedness of a topic i to the scientific portfolio of city c in time t is given by the formula:

$$Relatedness.Density_{i,c,t} = \frac{\sum_{j \in c, j \neq i} \phi_{ij}}{\sum_{j \neq i} \phi_{ij}} \times 100 \quad (2)$$

In a third step, we compute the scientific coherence of each city, which is simply the average relatedness density of all topics that can be found in the scientific portfolio of a given region (relatedness density is indicated as *RD* in Equation (3)):

$$Scientific.Coherence_{c,t} = \frac{\sum_{i \in c} RD_{i,c,t}}{\sum_{i \in c} i} \quad (3)$$

Based on these indicators of: first, entry/exit/maintenance rate; second, our measure of scientific coherence we then analyse the dynamics of scientific knowledge in Astrophysics, Biotech, Nanotech and Organic Chemistry, with a particular focus on patterns of specialisation and path-dependence in knowledge evolution.

3.4 Entry and exit models

In the next step, we want to estimate how relatedness influences in another way the scientific knowledge trajectory of cities in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry. We model knowledge dynamics as the process of entry, exit and maintenance of scientific topics in cities’ portfolios (i.e. as an evolving city–topic network). In our baseline specification, we regress the emergence of new scientific topics on their degree of relatedness with the scientific portfolio of cities, which is captured by the relatedness density variable (see Equation (2)). The basic econometric equation to be estimated can be written as follows:

$$Entry_{i,c,t} = \beta_1 relatedness.density_{i,c,t-1} + \beta_2 City_{c,t-1} + \beta_3 Topic_{i,t-1} + \varphi_c + \psi_i + \alpha_t + \varepsilon_{i,c,t} \quad (4)$$

Where the dependent variable $Entry_{i,c,t} = 1$ if a topic i that did not belong to the scientific portfolio of the city c in time $t - 1$ enters its

portfolio in time t , and is 0 otherwise; the key explanatory variable $relatedness.density_{i,c,t-1}$ indicates how related the potential new topic i is to the pre-existing scientific set of capabilities of c . This is our main variable of interest and we want to estimate its different impact across the four different fields. Therefore we run four different models, one for each field, with the same econometric specification and compare the size of the standardised $relatedness.density_{i,c,t-1}$ coefficient. We also use the same baseline specification to model the exit of topics over time.

Of course, we need to control for important characteristics at the city and topic levels. $City_{c,t-1}$ is a vector that summarises a range of observable time-varying city characteristics: city (scientific) size and specialisation. The scientific size is computed as the number of keywords that can be found in a city’s portfolio in a given field. We count all occurrences, even if words are used more than once. Specialisation is computed as an average location quotient, $Topic_{i,t-1}$ is a vector that summarises a range of observable time-varying technology characteristics. In our empirical analysis we only account for the size of the topic, computed as the number of occurrences of a topic in journal articles of a given field, φ_c is a city-fixed effect, ψ_i is a technology-fixed effect, α_t is a time-fixed effect, and $\varepsilon_{i,c,t}$ is a regression residual. We estimate Equation (4) by using a linear probability (OLS) regression. The main advantage of using LPM linear probability model is the simplicity of estimation and interpretation, but the use of logit/probit leads to similar average marginal effects (Angrist 2001). φ_c , ψ_i and α_t fixed effects are directly estimated by including dummy variables for each city, technology and time period that compose our panel and all the regression results are clustered at the city–technology level. Our panel consists of data for 200 cities and 1,000 topics (keywords) for each scientific field over the period 2000–12 (two-year period).

4. The dynamics of scientific knowledge in Astrophysics, Biotechnology, Nanotech and Organic Chemistry

In this section, we first describe the developments of the field by focusing on the prominent locations of research and the most important topics. We explore whether the differential growth rates of cities in terms of output are linked to distinct patterns in the dynamics of topics.

We then analyse the dynamics of scientific knowledge in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry from the essential process of the entry, exit and maintenance of key scientific topics in cities and patterns of specialisation and path-dependence in knowledge evolution from the level of average scientific coherence (within scientific fields and within cities).

4.1 Astrophysics

Astrophysics is characterised by a relatively stable hierarchy of research locations. The most important locations in the field (as measured by the total number of publications in the period under study) remain identical between 1996 and 2012. Cambridge, MA (USA) loses its position as the prime contributor in the field to Pasadena, CA (USA) in later years, but remains the overall top contributor in the period 1996–2012. Other small shifts are indicative of the ongoing globalisation of knowledge production, as is visible by the rise of Beijing from position 47 in 1996 to position 9 in 2012.

The most frequently used keywords in the field of Astrophysics show new topics in 2012 that were not present in 1996: digital sky

survey and Hubble-space-telescope. These topics are indicative of the use of new data infrastructures and technological infrastructures as drivers of new cognitive developments in the field. Other topics seem to lose some of their relevance in the field: galaxies, gas, photometry and universe move down the ranking of important keywords.

The analysis indicates that not only is there a high level of path dependency in knowledge production, but also that research locations tend to have capabilities to contribute to a wide range of topics. The relatedness analysis allows us to further specify the rise and fall of research locations with respect to their publication output in specific topics.

Fig. 1 plots the scientific coherence for all Astrophysics cities ($n=200$) for the years 2000 and 2010. We can see from Fig. 1 that the average relatedness in Astrophysics cities is very high. It means that the scientific portfolio of cities in this field is very coherent, with most of the topics produced being related to each other. That might signal an incremental, path-dependant mode of knowledge production in Astrophysics. The 45° line separates cities that experienced an increase in average relatedness (i.e. that increased the coherence of their scientific portfolio over time) above the line and those who experienced a decrease in average relatedness (below the line). We can see that not only is the level of scientific coherence very high, but that it also increased for most of the cities in the period 2000–10.

4.2 Biotechnology

Biotechnology shows more turbulent developments in terms of the prominence of research locations in the field. The ranking of cities shows two prominent newcomers in 2012 that were not yet present in the field in 1996: Singapore and Beijing. Also the movement of cities up and down the ranking is more pronounced than in Astrophysics. For example, Cambridge, MA is one the overall most important contributor in Biotechnology in the period under study, but it has dropped to place 17 in 2009. More dramatically, Zurich (Switzerland) (overall position 9) dropped from position 2 in the ranking in 1996 to position 135 in 2012.

The use of keywords in Biotechnology provides a first indication of the development of the field. Two prominent topics emerged after 1996: in-vitro and gene-expression. Several topics lose their relevance in the period under study: most importantly Enzymes. These developments are in agreement with previous studies that observed the emergence of new topics related to molecular biology (Krafft

et al. 2011). Almost all topics show large shifts in importance during the period under study.

Biotechnology is characterised by a strong relationship between the geography of knowledge production and the research topics under study (Heimeriks and Boschma 2014). Many topics only originate from a small number of locations. Biotechnology is much more rooted in local contexts, possible related to the socio-economic contexts of application (Heimeriks and Leydesdorff 2012). None of the prominent research locations contribute to all important topics in the field. In this respect, Biotechnology is characterised by a high level of specialisation.

The analyses show that the research locations in the field of Biotechnology that rise up the ranking contribute significantly to emerging topics that gain prominence in the period under study. In reverse, locations that move down the ranking contribute substantially to topics that lose importance. Further, within the context of a growing field, many newcomers manage to create a dominant niche for themselves. In Biotechnology, few research locations manage to maintain a comparative advantage in a particular topic over the entire period under study.

Fig. 2 plots the scientific coherence for all important cities contributing to Biotechnology research ($n=200$) for the years 2000 and 2010, as we did previously for Astrophysics cities. We can see a very different pattern emerging here. Compared to the very high average relatedness in Astrophysics cities, the coherence of the scientific portfolio of Biotechnology cities is much lower. This confirms the more dynamic, unpredictable type of knowledge development in this field. Looking at the 45° line, one can observe that the level of average relatedness remained very stable for most of the cities in the period 2000–10.

4.3 Nanotechnology

The journal *Nanotechnology* was included in the Science Citation Index in 1996. The journal was initially categorised as an Applied Physics journal, but developed increasingly into a central focus of attention within the field of Nanotechnology towards the end of the millennium. In the period 2000–3, Nanotechnology became a priority funding area in most advanced nations. As a consequence, in the period under study the field shows fast, turbulent growth. Only one of the prominent research locations in the period 1996–2012 was already participating in the year 1996: Cambridge, MA. By 2012, the field is dominated by Asian and American cities with Beijing, Seoul,

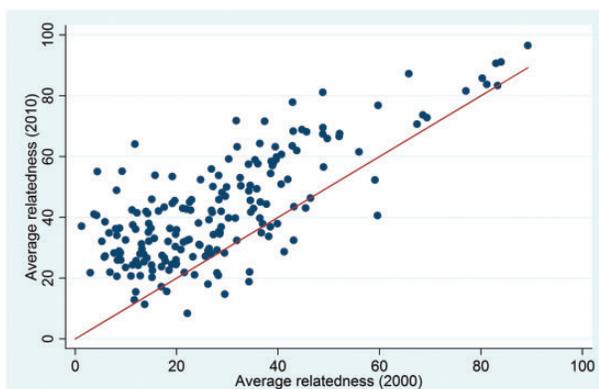


Figure 1. Scientific coherence in Astrophysics cities (2000 and 2010)

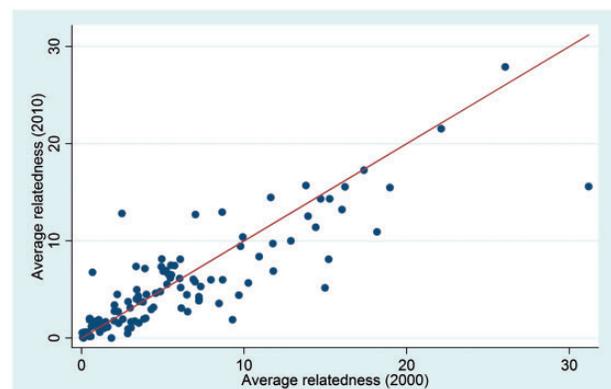


Figure 2. Scientific coherence in Biotechnology cities (2000 and 2010)

Berkeley, CA, Cambridge, MA and Singapore as most important locations.

The most turbulent cognitive developments among the fields are to be found in Nanotechnology. Only a handful of important keywords in 1996 rank among the most frequently used keywords in 2009: films, surface, carbon nanotubes and chemical-vapour-deposition. All other important topics, with nanoparticles and nanowires among the most prominent, emerged in later years.

Nanotechnology shows very high growth in the period under study, creating opportunities for many newcomers. Compared to Biotechnology, the range of topics for locations to contribute is much larger, despite the much larger size of the field in terms of the number of publications.

The rise of prominent research locations in this field also corresponds to the rise of the important topics in the field, such as Nanoparticles. Many important locations contribute to global high-growth topics. Furthermore, some research locations maintain comparative advantages over a longer period of time in a small number of topics. The analysis shows that all important locations have a comparative advantage on some topics in the period under study. In later years, Nanotechnology evolves towards a stable pattern of knowledge production: the concentration of research activities is high, cities produce more output, stability in the ranking is greater, and comparative advantages last longer.

As in Astrophysics, and unlike in Biotechnology, locations have capabilities to contribute to a wider range of topics. Unlike Astrophysics and Biotechnology, however, the growth of the field is associated with all the important topics.

Fig. 3 plots the scientific coherence for all Nanotechnology cities ($n = 200$) for the years 2002 and 2010. Here we use the year 2002 because that is the year in which the field really started. Again, we can see a different pattern from the one observed in Astrophysics and Biotechnology cities. The average relatedness in Nanotechnology cities was initially very low, but it then grew tremendously over time. Indeed, virtually all cities are above the 45° line, which indicates a growth in the coherence of the scientific portfolio of cities in the period 2002–10.

4.4 Organic Chemistry

In contrast to Nanotechnology, Organic Chemistry represents a long established field of research with a pattern of stable development and slow growth. The list of most important research locations in the field remains fairly stable, with some movement up and down

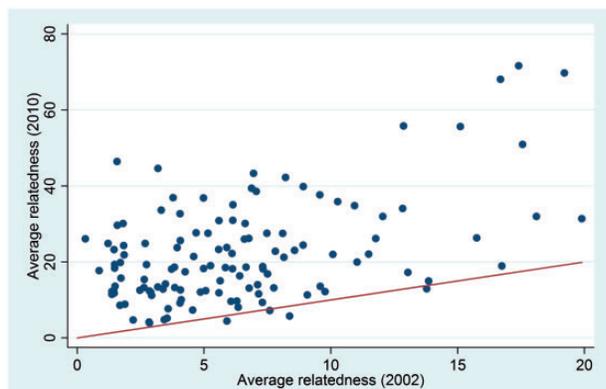


Figure 3. Scientific coherence in Nanotechnology cities (2002 and 2010)

the ranking but without important new entrants or exits in the field. The rise of Chinese research locations is also visible in this field. By 2012, Shanghai (China) has established itself as the newly dominant contributor in the field while Beijing moves to the third spot in the ranking, after Tokyo.

In Organic Chemistry, the important research locations contribute to a wide range of topics. Nevertheless, only few important research locations manage to maintain a comparative advantage over the entire period in a number of topics.

A stable cognitive development is visible in Organic Chemistry. There are neither new entrants nor exits among the most important keywords. However, as in the previous cases, many topics show shifts in importance during the period under study. Only very few locations manage to maintain a comparative advantage in certain topics over the entire period.

Fig. 4 plots the scientific coherence for all important Organic Chemistry cities ($n = 200$) for the years 2000 and 2010. We can see from Fig. 4 that, as in Astrophysics, the scientific coherence is high. Even though the scientific portfolio of cities in this field is less coherent than that in Astrophysics, it still indicates that the topics produced in a city are closely related to each other. That might also signal the maturation of the field, based on increasingly incremental new knowledge production. The 45° line reveals that there has been relatively little change in average relatedness over time. More or less the same number of cities can be found above and below the line.

4.5 The co-evolution of locations and topics in different fields

The increasing number of publications and the rising number of contributing locations indicate an on-going globalisation and the consequent escalation in scientific competition (UNESCO 2010). However, the analyses presented here highlight the distinct knowledge dynamics in different fields. In dynamic (emerging) fields, with high growth rates (e.g. Biotechnology and Nanotechnology); any entrance barriers which hinder new organisations from contributing are low. Often diverging skills, infrastructures and methods are used in these circumstances (Bonaccorsi 2008). To make a more systematic comparison of differences in terms of internal coherence of scientific portfolios of cities across fields and over time, we compute the average internal coherence in each field, for each year (see Fig. 5).

Astrophysics is the most coherent field, characterised by the highest scientific coherence in cities, followed by Organic Chemistry, Nanotechnology and Biotechnology. Nanotechnology

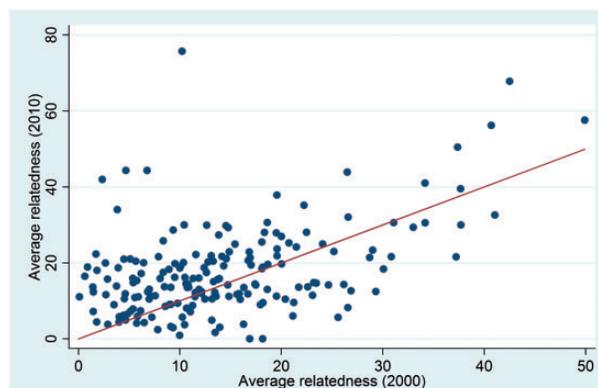


Figure 4. Scientific coherence in Organic Chemistry cities (2000 and 2010)

has changed dramatically over time. This development coincides with the surge in funding of Nanotechnology when it became a priority funding area in most advanced nations in the period 2000–3 (Leydesdorff and Schank 2008).

The results further confirm our hypothesis that fields characterised by high levels of mutual dependence and low levels of task uncertainty exhibit accumulative patterns of knowledge developments where different locations mutually contribute to the same range of topics. This insight can be further elaborated by studying patterns of entry, exit and maintenance of keywords in cities over time. Instead of counting and comparing the raw numbers for entry and exit, which would not account for differences in size of the different fields, our analysis focuses on the rates of entry, exit or maintenance. Assuming that the spatial dynamics of knowledge in a given field can be defined as an evolving two-mode network based on pairs of city–topics (Boschma et al. 2014) we compute the maintenance rate as the share of city–topics linkages in t that are maintained in $t + 1$.

Fig. 6 shows that Astrophysics is the most stable field, with a maintenance rate above 0.4. This rate is increasing over time. Organic Chemistry is the second most stable field (maintenance rate above 0.2) and is very stable over time. Although Nanotechnology was the least stable field in 2000 (below 0.1), its maintenance rate increased significantly over time, and it is now comparable with Organic Chemistry (above 0.25). Biotechnology also started with a low level of stability. It is still a very dynamic field characterised by high levels of entry and exit of topics in cities.

As shown, the scope of opportunities for research locations around the world to contribute within the constraints of the existing body of knowledge is different for each field. Biotechnology showed the highest level of local specialisation while Astrophysics provides a wide range of research topics for the most important organisations in the field. This is also the case for Nanotechnology in later years, although to a lesser extent.

5. Modelling knowledge dynamics: The different role of relatedness across scientific fields

5.1 The model

We estimate the different way in which relatedness influences the scientific knowledge trajectory of cities in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry. We model knowledge dynamics as the process of entry, exit and maintenance

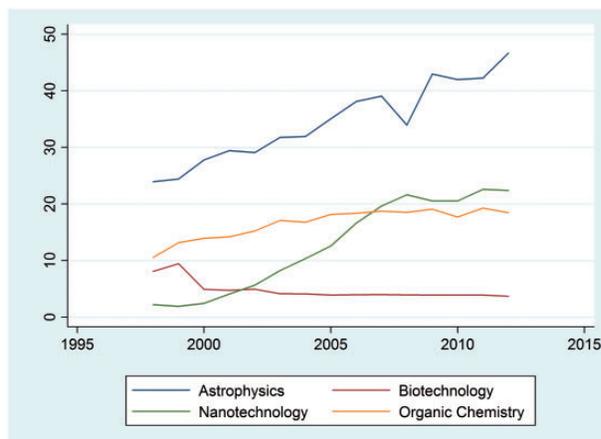


Figure 5. Scientific coherence across fields

of scientific topics in cities' portfolio (i.e. as an evolving city–topic network). In our baseline specification, we regress the emergence of new scientific topics on their degree of relatedness to the scientific portfolio of cities, which is captured by the relatedness density variable (see Equation (2)). Table 3 provides some summary statistics of the variables used in the econometric analysis.

5.2 Entry model

Table 4 presents the results for the estimation of Equation (4) for each of the four scientific fields. For all the different fields, relatedness density has a positive and significant effect on the probability that a new topic enters in the scientific portfolio of a city. It indicates that all, to some extent, the fields that we analysed exhibit a pattern of path- and place-dependence. In that respect we confirm and extend the results of Boschma et al. (2014) using a more conservative econometric specification (three-way fixed effects model to take into account time-unvarying omitted variable bias at the city and topic levels) and more importantly, analysing other scientific fields.

Although relatedness seem to be a general driving force behind scientific knowledge dynamics, the magnitude of the path- and place-dependence varies enormously across fields. Looking at the size of the standardised 'relatedness density' coefficient, we can see that Astrophysics is the most path- and place-dependent field ($\beta = 0.0820$; 95% confidence interval (CI) = 0.0803 – 0.0838). In relative terms, Biotechnology is the least path-dependent with a coefficient for relatedness of 0.0079 (95% CI = 0.0072 – 0.0083). A similar, intermediate level of path-dependence seem to be reached by Nanotechnology and Organic Chemistry, with a coefficient for relatedness density of 0.0168 (95% CI = 0.0152 – 0.0185) in the case of Nanotechnology and (slightly higher) of 0.0210 (95% CI = 0.0197 – 0.0222) for Organic Chemistry. None of the CIs of the relatedness density coefficients of different fields overlap, which make us confident about the statistical significance of the difference between coefficients. These results are consistent with the econometric specifications that omit fixed effects at the city and topic levels.

The control variables (city size, topic size, specialisation of cities) tend to show the expected sign and significance (see Table 4). An increase in city size also increases the probability of entry (of any new topic) in all fields (not significant at the 5% level for Astrophysics) except for Biotechnology, where the effect is negative but largely not significant. Topic size also predicts the entry (in any city). Again, only the coefficient for Biotechnology is not significant. Surprisingly, specialisation has a positive impact on the probability

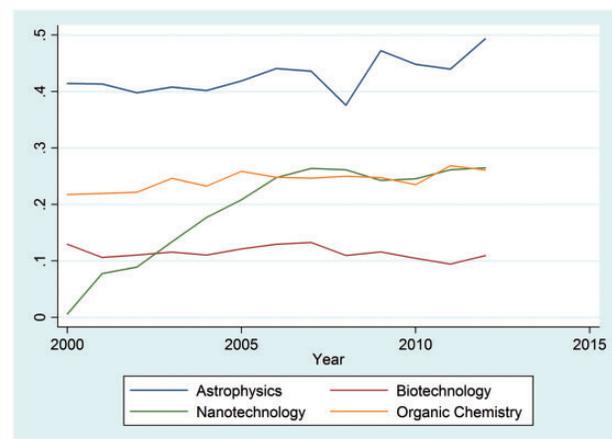


Figure 6. Maintenance

of entry for Astrophysics and Biotechnology, while it is not significant in Nanotechnology and it has a negative impact for Organic Chemistry.

5.3 Exit model

We now run Equation (4), using ‘exit’ as a dependent variable instead of ‘entry’. The main variable of interest ‘relatedness density’ and the control variables are strictly the same. Table 5 presents the results of the analysis of the driving forces behind the exit dynamics for each of the four scientific fields. For all the different fields, relatedness density has a negative and significant effect on the

probability that a new topic exits the scientific portfolio of a city. As for entry models, the magnitude of the coefficient for relatedness density varies significantly across fields. The most path- and place-dependent field is again Astrophysics, followed by Organic Chemistry. But this time, the magnitude of the coefficient is comparable for the two emerging fields of Biotechnology and Nanotechnology. These results are consistent with the econometric specifications that omit fixed effects at the city and topic levels.

The control variables for city size is only negative and significant (expected sign) in the case of Biotechnology, but this is probably due to our conservative fixed effect specification (see Table 5). Once we relax the fixed effects, the coefficient is again negative and

Table 3. Summary statistics

Variables	Obs.	Mean	Std. Dev.	Min.	Max.
Astrophysics					
Entry	637731	0.1533374	0.3603127	0	1
Relatedness density	1000000	53.0854	26.39476	0	100
City size	1000000	1300.522	1947.903	0	17194
Topic size	1000000	260.1044	448.8643	0	7796
Specialisation	1000000	10.24179	25.36823	1.33445	443.8924
Biotechnology					
Entry	773736	0.0292736	0.1685724	0	1
Relatedness density	1000000	13.3333	13.64601	0	100
City size	1000000	57.464	60.96019	0	492
Topic size	1000000	11.4928	21.69576	0	417
Specialisation	1000000	59.00957	90.21467	4.774038	1479.889
Nanotechnology					
Entry	758703	0.0657978	0.2479285	0	1
Relatedness density	1000000	23.84461	23.30484	0	100
City size	1000000	153.152	261.9265	0	2792
Topic size	1000000	30.6304	78.04952	0	1421
Specialisation	1000000	39.65747	106.713	1.880352	1886.5
Organic chemistry					
Entry	727248	0.0746417	0.2628124	0	1
Relatedness density	1000000	33.28048	20.09522	0	100
City size	1000000	174.874	211.6843	0	2529
Topic size	1000000	34.9748	71.26629	0	1704
Specialisation	1000000	18.81473	38.69393	1.745426	1114.421

In econometric estimations presented in this paper, relatedness density has been standardised by first subtracting the mean from the value of each observation and then dividing the resulting difference by the standard deviation

Table 4. Entry dynamics in four different fields

Dependent variable is: Entry	Astrophysics	Biotechnology	Nanotechnology	Organic Chemistry
Relatedness density	0.0820996** (0.0009077)	0.0079124** (0.0003302)	0.0168617** (0.000845)	0.0210179** (0.0006255)
City size	0.00000293 (0.00000170)	-0.0000571 (0.00000936)	0.0000663** (0.00000444)	0.0000476** (0.00000640)
Topic size	0.0000894** (0.00000511)	0.0000913 (0.000056)	0.0007438** (0.0000189)	0.0004785** (0.0000331)
Specialisation	0.0000639** (0.000013)	0.0000144** (0.00000232)	0.00000377 (0.00000228)	-0.0000699** (0.00000590)
Period fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Topic fixed effects	Yes	Yes	Yes	Yes
N	637731	773736	758703	727248
R ²	0.1344	0.0540	0.1224	0.0996

Dependent variable entry = 1 if a given topic (n = 1000) enters scientific portfolio of a given city (n = 200) during corresponding 2-year window (n = 4), and 0 otherwise. ‘Relatedness density’ variable is standardised so that it can be compared across models. All independent variables are lagged by one period

Coefficients are statistically significant at *p < 0.05; and **p < 0.01 level Heteroskedasticity-robust standard errors (clustered at city–technology level) given in parentheses

Table 5. Exit dynamics in four different fields

<i>Dependent variable is: Exit</i>	Astrophysics	Biotechnology	Nanotechnology	Organic chemistry.
Relatedness density	−0.1733424** (0.0031749)	−0.0239141** (0.0030116)	−0.0271512** (0.0051883)	−0.0576634** (0.0006255)
City size	0.00000198 (0.00000133)	−0.0001571* (0.0000738)	0.0000294* (0.0000126)	−0.00002 (0.0000134)
Topic size	−0.0000355** (0.00000398)	−0.0001451 (0.0001715)	−0.0001761** (0.0000239)	−0.0002417** (0.0000302)
Specialisation	−0.0006563** (0.0002468)	−0.0001919* (0.0000784)	−0.0000704 (0.0000581)	−0.0001556 (0.0002342)
Period fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes
Topic fixed effects	Yes	Yes	Yes	Yes
N	637731	773736	758703	727248
R ²	0.2358	0.1953	0.3077	0.2462

Dependent variable exit = 1 if a given topic ($n = 1000$) exits scientific portfolio of a given city ($n = 200$) during corresponding 2-year window ($n = 4$), and 0 otherwise. 'Relatedness density' variable is standardised so it can be compared across models. All independent variables are lagged by one period

Coefficients are statistically significant at * $p < 0.05$; and ** $p < 0.01$ level

Heteroskedasticity-robust standard errors (clustered at city–technology level) given in parentheses

significant. In all cases, large topics tend to remain longer in cities (not significantly for Biotechnology). Specialisation always has a negative impact on the probability of exit but it is only significant in the cases of Astrophysics and Biotechnology.

6. Discussion and policy implications

As a consequence of increasing globalisation, and competition, there has been a growing emphasis on the dynamics of knowledge production (Cowan et al. 2000). Governments, both nationally and regionally, need to ensure that the local knowledge base is strong in order to ensure global competitiveness (Foray 2006). The analyses presented here have major implications for research and innovation policy with respect to the local knowledge base. The innovation systems literature emphasises that because science and innovation are locally embedded, practices in research and innovation policies cannot be simply copied between countries and fields (Asheim et al. 2006). The analyses in this paper allow us to further specify how research fields exhibit distinct and localised knowledge dynamics that can be expected to respond differently to government interventions.

Our analyses show that the variety of topics that is potentially available to researchers is very different among fields, as are the path- and place-dependent constraints. Furthermore, the entry barriers for newcomers are different among fields of knowledge production. Consequently, the opportunities to construct unique locational advantages in relation to the global body of knowledge are very different among fields. This is why the idea that cities or regions should specialise in their current areas of comparative advantage should take identifying the related variety into account. The challenge is not to pick a few winners among the locations and topics, but rather to facilitate the emergence of more winners by enabling them to nurture new research activities. Our research suggests that research activities with lower levels of uncertainty and higher levels of knowledge accumulation are more resilient over time.

This study focused on the dynamics of knowledge as made visible by scientific journal publications. While the smart specialisation agenda refers to both knowledge and innovation dynamics (Foray et al. 2012), there are good reasons to focus on the localised production and accumulation of scientific knowledge.

First, economic opportunities are relatively invariant across different regions (Breschi et al. 2003), while knowledge bases are more likely to differ according to their geographical locations. Indeed, it has been shown that the knowledge production and accumulation are more geographically concentrated than economic activities (Florida 2005). Thus, the unique innovative potential of regions and cities is strongly linked to their ability to develop an institutional context that facilitates the production and the accumulation of knowledge. The geographical patterns found here in relation to different evolutionary patterns of the global knowledge base, are consistent with earlier findings that market developments across sectors are largely determined by the level of accumulateness of the knowledge base (Malerba and Orsenigo 2002).

Furthermore, a policy focus on knowledge dynamics rather than an exclusive focus on the innovation reduces the risk of favouring vested economic interests and allows for exploration of new economic opportunities based on unique regional knowledge characteristics. This is especially important for the development of radical technologies. Radical science-based technologies rarely originate from industry incumbents because long time frames suppress incumbents' ability to meet short-term goals (Anderson and Tushman 1990; Christensen 1997). Consequently, research universities and government labs are expected to initiate new developments (Mazzucato 2011). Perez and Soete (1988) argue that scientific research at universities is essential for contributing to the knowledge base that is needed for new technological paradigms.

There are clear territorial implications from the path- and place-dependent evolution of knowledge outlined in this paper. There is a clear need for regions to adequately adapt to new conditions by maintaining flexibility and diversity in the regional knowledge base in order to make use of new developments in the global knowledge base. Thus, the evolutionary approach particularly implies policy attention at both the local and global levels. Furthermore, such a perspective implies a more dynamic view of regional growth, in contrast with more traditional static, snapshot-like views (Laranja et al. 2008).

A better understanding of the nature of the evolving local knowledge base can further inform decision-making on investment in research and innovation, thus taking into account the broader 'policy mix' influencing innovation in regions (Flanagan et al. 2011). While

scientific publications only represent a part of the codified knowledge base of a region, they do provide a rich source of information about the local knowledge base that cannot be easily obtained from other sources, especially concerning knowledge developments that are not yet commercially exploited.

The findings of this study raise many new questions that need more careful attention in further research. For example, this study was based on two central tendency journals representing an entire field. Inevitably, part of the observed changes in the field can be attributed to journal-specific dynamics. Furthermore, part of the knowledge developments will take place outside the selected journals in these fields and are not accounted for in this study. Nevertheless, we expect that the changes we observed accurately reflect the dynamics of the fields to a large extent, because the results are consistent with previous studies (Heimeriks and Leydesdorff 2012).

Moreover, only a few representative scientific fields were used in this study to demonstrate the specialisation patterns associated with different fields. Consequently, the results do not provide a complete picture of the overall specialisation of cities. As such, these issues require more attention in the future.

7. Conclusions

In this study, we explored the specialisation patterns of knowledge production in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry. The question underlying this study was whether the rise and fall of research locations can be attributed to their specialisation pattern of scientific knowledge production.

The analyses showed that path- and place-dependent processes of knowledge production can be identified in all fields. Confirming Hypothesis 1, the analysis reveals that locations show a pattern of specialisation over time. We account for these specialisation patterns by assuming that each topic of research requires local capabilities (e.g. skills, infrastructures and supporting institutions), and that a research location can only contribute to topics for which it has all the requisite capabilities.

In conformity with Hypothesis 2, the specialisation patterns of cities offer opportunities for further improvements in related topics, and discourage the creation of knowledge on topics unrelated to the local knowledge base.

Topics (and fields in general) differ in the number and specific nature of the capabilities they require, as research locations differ in the number and nature of capabilities they have. Topics that require more capabilities will be accessible to fewer locations (as is the case in most topics in Biotechnology), while cities that have more capabilities (as is the case in Astrophysics) will have what is required to contribute to more topics (i.e. will be more diversified).

The patterns of research activities differ systematically across the scientific fields under study. Furthermore, these patterns are remarkably similar across locations within each scientific field, thus confirming Hypothesis 3. Two patterns of specialisation are identified. The first represents a turbulent pattern: concentration of research activities is low, knowledge-producing organisations are small in terms of output, stability in the ranking is low and comparative advantages are short lasting. Relatedness among topics is low, and as a consequence locations that specialise in certain topics face high levels of uncertainty in exploring new topics.

The second pattern is stable: concentration of research activities is higher than in the first group, research locations are larger, stability in the ranking is greater, and comparative advantages last longer.

Relatedness among topics is high, and locations that specialise in certain topics can easily branch into related topics of research. As such, task uncertainty is low.

The former group comprises Biotechnology, while the latter includes Astrophysics. Astrophysics is the most coherent field, characterised by the highest average relatedness in cities. Organic Chemistry has an intermediate position, and Nanotechnology develops towards a stable pattern of knowledge production with lower levels of task uncertainty. This development coincided with the surge in funding of Nanotechnology in the period 2000–3 (Leydesdorff and Schank 2008).

These results further confirm Hypothesis 3, which states that fields characterised by high levels of mutual dependence and low levels of task uncertainty exhibit accumulative patterns of knowledge developments where different locations mutually contribute to the same range of topics. These patterns are clearly related to the available repertoire of related topics in the different fields.

This study showed that policy attention to the localised production and accumulation of knowledge is important. Knowledge bases differ according to their geographical locations and the innovative potential of cities relies on the ability to develop an institutional context that facilitates the production and accumulation of knowledge. We specify how research fields exhibit distinct and localised knowledge dynamics that can be expected to respond differently to government interventions, because the accumulation of knowledge and the opportunities to diversify into related knowledge differ greatly among fields of knowledge.

In a globalising knowledge economy, where all regions are increasingly exposed to transformation pressure, the regional capability to innovate and to adapt becomes increasingly important. Thus, a smart specialisation strategy should focus on the long-term building up of the local knowledge base that allows for the accumulation of knowledge in the complex interaction between global and local processes.

Cities and regions specialise because of the cumulative and place-dependent character of knowledge production, but that does not imply that they should necessarily choose a specialisation (Hausmann 2013). Specialisation is only smart when it allows for future diversification into related knowledge.

In general, smart specialisation strategies need to take into account the two dependencies that this study brought to the fore: the path dependencies of global knowledge accumulation and the place dependencies of local capabilities. In the accumulative fields of knowledge production, where research locations have the capabilities to contribute to many (related) topics, the number of new entrants tends to be low. However, a key finding here is that research activities with lower levels of task uncertainty and higher levels of knowledge accumulation are more resilient over time. These fields are characterised by low levels of uncertainty about the future research opportunities and thus provide long-term perspectives of related diversification.

Notes

1. Codified knowledge refers to knowledge so articulated and clarified that it can be expressed in a particular language and recorded on a particular medium.
2. For example, see <<http://www.leydesdorff.net/jcr05>> accessed 9 Oct 2015, where the data is provided for the citation environments of all the journals included in the Science Citation Index and the Social Science Citation Index.

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