How Smart is Specialisation? An Analysis of Specialisation Patterns in Knowledge Production

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Abstract

We examine the regional specialisation patterns of knowledge production in Astrophysics, Biotechnology, Nanotechnology and Organic Chemistry between 1996 and 2012. The patterns of specialisation differ systematically across scientific fields, but are remarkably similar across cities within each field. Biotechnology follows a turbulent pattern: concentration of research activities is low, knowledge production in cities is of small size in terms of output, stability in the ranking is low and comparative advantages are short lasting. Relatively few related topics are available for research locations. Astrophysics and (in later years) Nanotechnology, show a stable pattern: concentration of research activities is high, cities produce more output, stability in the ranking is greater, and comparative advantages last longer. For research locations many related topics are available. Organic Chemistry has an intermediate position. The fields thus require different smart specialisation strategies that take into account the differences in accumulation and relatedness.

Keywords: *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 & Ortega-Argilés 2013).

It can be difficult for policymakers 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 – that is, on their comparative advantage.

The question is whether there is a 'smart specialisation' alternative to policies that spreads investments thinly across many topics of research, and, as a consequence, not making much of an impact in any one area (Todtling & Trippl, 2005). A more promising strategy appears to be to encourage investment in programs that will complement existing skills and infrastructures to create future capability and comparative advantage (Hausmann & Hidalgo, 2009).

Of course, cities and regions do specialise. The cumulative and path-dependent character of knowledge production makes it also place-dependent (Heimeriks & 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.

But, according to Hausmann the idea that cities and regions actually do specialise, and that therefore they should specialise, is a very wrong and dangerous idea (Hausmann, 2013). Hausmann argues that specialisation at the individual level actually leads to diversification at a higher level. It is precisely because organisations specialise that cities and regions diversify.

While there are many studies to show that regional specialisation occurs, 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 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 makes it also place-dependent. This implies that locations

of research are likely to specialise over time (Heimeriks & 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 & 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 for 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, 2013) and differ in the extent to which the codified body of knowledge is accumulative (Bonaccorsi 2008).

The 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 key words. We explore whether differential growth rates of cities in terms of output are linked to distinct patterns in the dynamics of topics. 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 order to measure knowledge dynamics in different fields, we use key-words in scientific publications over a long period of time, in order to identify the rise and fall of key scientific topics. Inspired by the 'product space' concept (Hidalgo et al., 2007), we construct a 'scientific space' in which the degree of relatedness between topics in different fields is determined by means of co-occurrence analysis (Boschma, Heimeriks, & Balland, 2014). This allows us to specify the role of relatedness in specialisation patterns among different fields. We expect that patterns of specialisation will be much more pronounced in fields that are characterised by a

variety of relatively unrelated topics. Furthermore, we expect that fields differ in the number and specific nature of the capabilities they require. Fields that require more capabilities will be accessible to fewer locations, while research locations that have more capabilities will be able to contribute to more topics (i.e., will be more diversified). 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 & 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 & Foray, 2002; Heimeriks & Vasileiadou, 2008). The term 'knowledge-based economy' stems from this fuller recognition of the place of organised knowledge 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 & 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 calls them, as the building blocks of an evolutionary approach to knowledge dynamics (David, 1994). These evolutionary dependencies in knowledge and locations are clearly related. Particular locations are characterised by particular knowledge developments building 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 one 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 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 utilized (accepted, criticized, and rejected) by others. Science is thus a global, collective and distributed system where researchers position themselves in with respect to the global knowledge base (Fujigaki 1998). This global body of scientific codified knowledge thus 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. Due to its 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, organizational practices and institutions (Arthur 1989).

Moreover, new scientific topics emerge and new important locations of research also appear frequently in a globalizing world. When locally embedded knowledge is combined in novel ways with codified and accessible external knowledge, new knowledge and ideas can be created (Heimeriks & Boschma, 2014). Consequently, new knowledge creation 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 have crucial implications for a spatial analysis of knowledge dynamics, and the associated rise and fall of research locations. The importance of space 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).

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. The topic repertoire of most locations comprises only a small subset of the range of recombinant possibilities that define knowledge space, and there are costs associated with search in that space (Heimeriks & Boschma, 2014; Rigby, 2013). These costs are related to the topography of knowledge space that Kauffman (1993) imagines as a fitness landscape where knowledge claims are characterized 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. As locations specialise in particular competences, these 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 to cope by non-local agents, as geographical distance may form an insurmountable barrier for the transfer of tacit knowledge

However, different scientific fields can be expected to constrain and facilitate the local opportunities of researchers to different degrees. Antonelli (1999) suggests that knowledge production is the result of a complex process of the creation of new knowledge building upon not only 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. Knowledge production thus 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). Also, fields of research 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 & Leydesdorff, 2012).

As consequence, we expect different patterns of local specialisation over time among different 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 are fundamentally uncertain in that outcomes are not repetitious and predictable. In fields of knowledge that are highly cumulative with 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, coordination mechanism of expensive infrastructures can be legitimised more easily for stable fields of knowledge production with 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 & 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 & Frenken, 2009).

In analogy with Schumpeterian patterns of innovation, we expect ‘Schumpeter Mark I' and 'Schumpeter Mark II' types of knowledge development (Malerba & 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.

Reversely, we expect that fields characterised by high levels of mutual dependence and low levels of task uncertainty to be exhibit very accumulative patterns of knowledge developments where different locations mutually contribute to the same range of topics. Consequently, stability in the ranking is greater, and comparative advantages can be expected to last longer.

3. Data and context

Our objective is to understand the specialisation patterns at different locations that emerge in different fields. The starting point of this paper is that the dynamics of scientific knowledge is a path and place dependent process (Heimeriks & Boschma, 2014), and that the current research portfolio of a city influences the further capacity to produce knowledge. However, these processes of path and place dependence are likely to differ systematically among different fields of knowledge. We aim to evaluate the impact of scientific relatedness on the patterns of specialisation at the city level in different fields. Our methodology follows the "product space" framework, which integrates network science to macroeconomic theories in order to understand the uneven development of countries (Hausmann and Klinger, 2007; Hidalgo et al., 2007). This framework develops a 2-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 2-mode network is based on pairs of city-topics constructed from publication records in different fields from 1996 to 2012.

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 & 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 between 1996 and 2012. Each pair of journals is selected as representative by its continuous presence in the core set of journals representing the field[1].

All data from these fields as retrieved from the ISI Web of Science could be organised in a relational database as the basis for the organisational analysis. The data contains the addresses as identified by the ISI Web of Science. The database thus 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. Several indicators based on key words have been developed to trace the development of science (e.g. 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 key words and their co-occurrences as the observable variation.

Context

[1] For example, at http://www.leydesdorff.net/jcr05 , the data is provided for the citation environments of all the journals included in the Science Citation Index and the Social Science Citation Index.

The cases for our empirical operationalization 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 Astrophysics and Organic Chemistry that are included in the analysis for comparison (Table 1).

Field	Journal	Number of Articles
Astrophysics	ASTROPHYSICAL JOURNAL	36572
	ASTRONOMY & ASTROPHYSICS	28531
Biotechnology	BIOTECHNOLOGY AND BIOENGINEERING	5873
	JOURNAL OF BIOTECHNOLOGY	3508
Nanotechnology	NANOTECHNOLOGY	7494
	NANO LETTERS	9421
Organic Chemistry	JOURNAL OF ORGANIC CHEMISTRY	23848
	ORGANIC LETTERS	18420

Table 1. The central tendency journals and number of articles per field.

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 like 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 importance 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 knowledge (Heimeriks & Leydesdorff, 2012). The combination of problem variety, instability, and multiple orderings of their importance with technical standardization 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 & 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 & Thoma 2007). Nanotechnology is highly interdisciplinary (Leydesdorff & Schank 2008) and 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).

Organic Chemistry knowledge development 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 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 (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, while fields characterised by high

levels of mutual dependence and low levels of task uncertainty to be exhibit very accumulative and stable patterns of knowledge developments.

		mutual dependence	
		high	**low**
task uncertainty	**high**	Nanotechnology	Biotechnology
	low	Astrophysics	Organic Chemistry

Table 2. Hypothesised position of the different fields along the dimensions "task uncertainty" and "mutual dependence".

4. The dynamics of scientific knowledge in Astrophysics, Biotech, 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 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 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 Measuring scientific coherence

Analysing the level of average scientific coherence requires three main steps. Scientific coherence describe, 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 key-words in a specific field. In this paper, we use a simple and normalized measure of relatedness based on the co-occurrences of key words within journal articles. We use the Jaccard index to account for the number of occurrences of each key-word. With occ_{ij} denoting the total number of times *i* and *j* co-occur in the same journal article, and occ_i denoting the total number of occurrences of *i*, the relatedness $\varphi_{i,j,t}$ between each topic *i* and *j* is given by:

$$\varphi_{i,j} = \frac{occ_{ij}}{occ_i + occ_j - occ_{ij}} \tag{1}$$

As a result, the measure is symmetric and $\varphi_{i,j,t} \in [0,1]$. 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 $\varphi_{i,j,t}$ 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 following formula:

$$RELATEDNESS\_DENSITY_{i,c,t} = \frac{\sum_{j \in c, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} \times 100 \qquad (2)$$

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 the equation).

$$SCIENTIFIC\_COHERENCE_{c,t} = \frac{\sum_{i \in c} RD_{i,c,t}}{\sum_{i \in c} i} \qquad (3)$$

Based on these indicators of (1) entry/exit/maintenance rate and (2) 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.

4.2 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 between 1996-2012. Other small shifts are indicative of the on-going globalization of knowledge production, as is visible by the rise of BEIJING, CHINA 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 not only that there is 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.

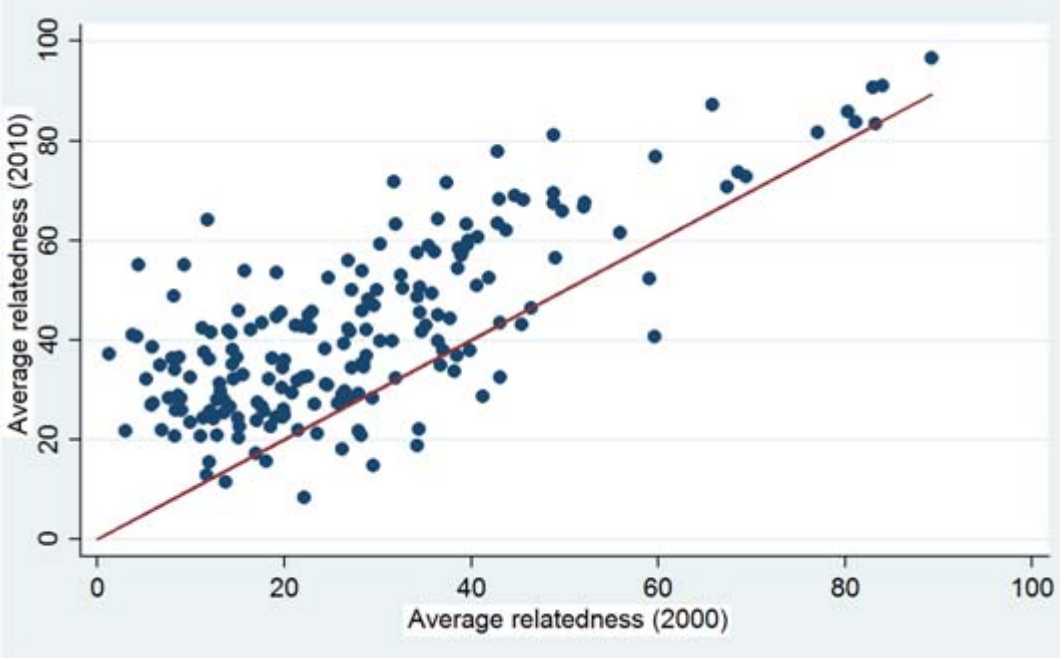

Figure 1. Scientific coherence in Astrophysics cities (2000 and 2010)

Figure 1 plots the scientific coherence for all Astrophysics cities (n=200) for the year 2000 and the year 2010. We can see from figure 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 separate 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 the

level of scientific coherence is very high, but it also increased for most of the cities from 2000 to 2010.

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 newcomer 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, USA 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 keywords in Biotechnology provide 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 new topics emerging 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 & Boschma 2014). Many topics only originate from a small number of locations. Biotechnology is much more rooted in local contexts, possible related to socio-economical contexts of application (Heimeriks & 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. Reversely, locations that move down the ranking contribute substantially to topics that lose importance. Furthermore, 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 over the entire period under study in a certain topic.

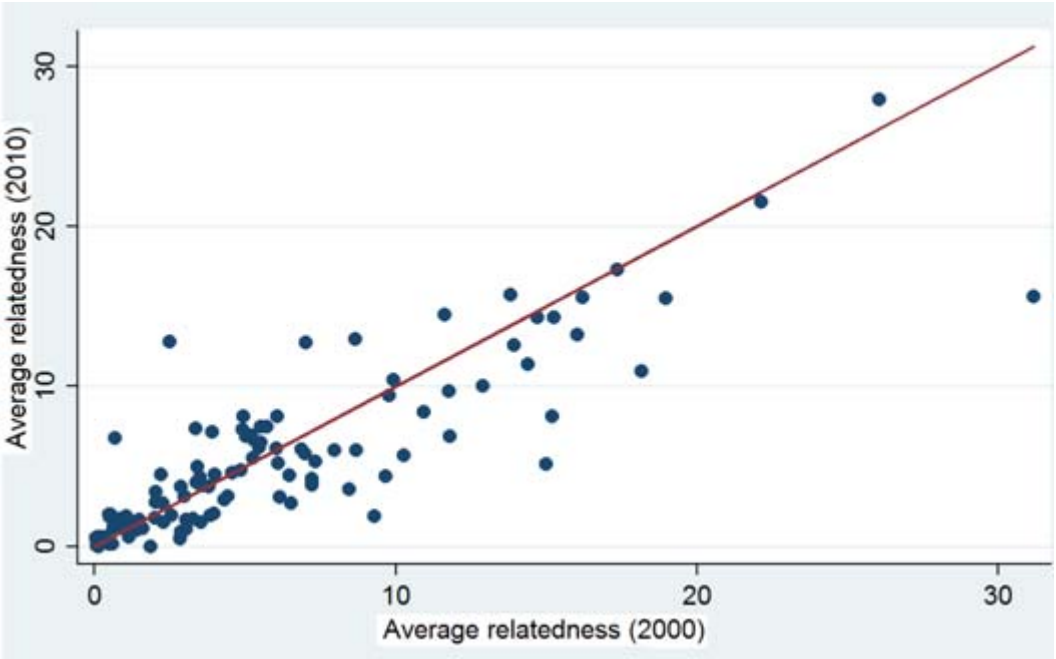

Figure 2. Scientific coherence in Biotech cities (2000 and 2010)

Figure 2 plots the scientific coherence for all important cities contributing to Biotechnology research (n=200) for the year 2000 and the year 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 from 2000 to 2010.

4.3 Nanotechnology

The journal Nanotechnology was included in the Science Citation Index in 1996. The journal was initially part of the field of "applied physics" journals, but developed increasingly into a central focus of attention within the field of Nanotechnology towards the end of the millennium. In the period 2000-2003, nanotechnology became a priority funding area in most advanced nations. As a consequence, in the period under study the field shows a development of turbulent fast growth. Only one of prominent research locations in the period 1996 and 2012 was already participating in the year 1996; CAMBRIDGE MA, USA. By 2012, the field is dominated by Asian and American cities with BEIJING, CHINA SEOUL, SOUTH KOREA, BERKELEY CA, USA, CAMBRIDGE MA, USA and SINGAPORE, 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-VAPOR-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 number of publications.

Also in this field, the rise of prominent research locations 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. Like 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.

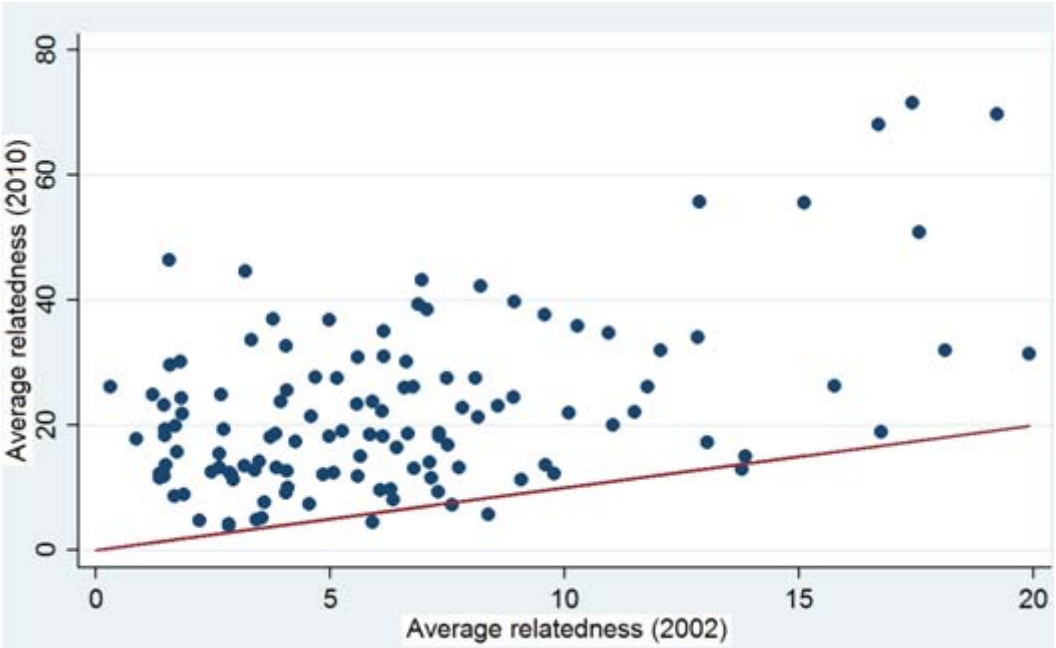

Figure 3. Scientific coherence in Nanotech cities (2002 and 2010)

Figure 3 plots the scientific coherence for all Nanotechnology cities (n=200) for the year 2002 and the year 2010. Here we use the year 2002 because this is the year when the field really started. We can see again a different pattern from the one observed in Astrophysics and Biotechnology cities. The average relatedness in Nanotechnology cities was very low at the beginning but then it 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 from 2002 to 2010.

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 the ranking but without important new entrants or exists in the field. Also in this field the rise of Chine research locations is visible. By 2012, SHANGHAI, CHINA has established itself as the newly dominant

contributor in the field while BEIJING, CHINA moves to the third spot in the ranking, after TOKYO, JAPAN.

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. Among the most important keywords, no new entrants nor exists are present. However, like 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.

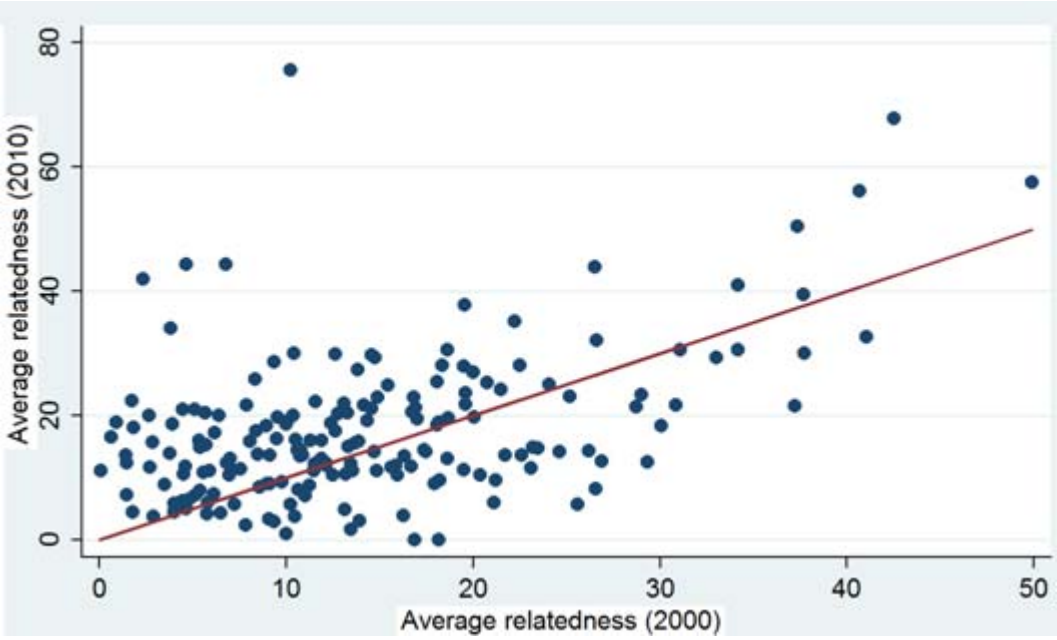

Figure 4. Scientific coherence in Organic Chemistry cities (2000 and 2010)

Figure 4 plots the scientific coherence for all important Organic Chemistry cities (n=200) for the year 2000 and the year 2010. We can see from figure 4 that, as in Astrophysics, the scientific coherence is high. Even though the scientific portfolio of cities in this field is less coherent than 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 globalization 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 (such as Biotechnology and Nanotechnology); entrance barriers are low for new organisations to contribute. Often diverging skills, infrastructures and methods are used in these circumstances (Bonaccorsi 2008). To compare more systematically 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 Figure 5).

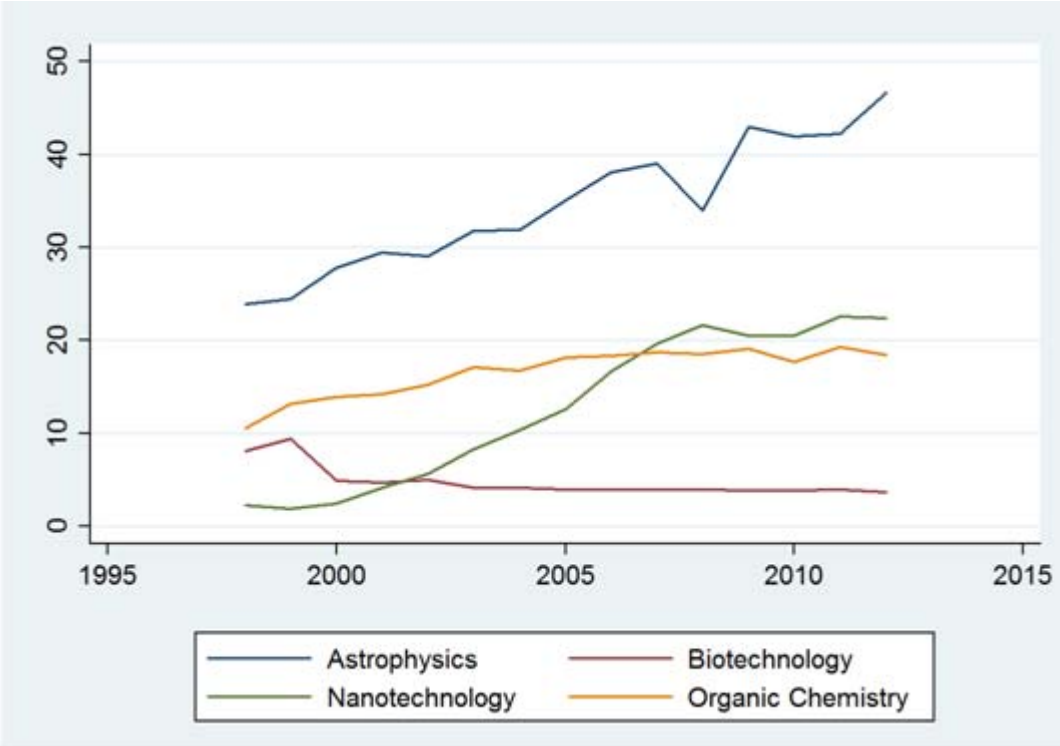

Figure 5. Scientific coherence across fields

Astrophysics is the most coherent field, characterised by the highest scientific coherence in cities, followed by Organic Chemistry, Nanotechnology and Biotechnology. Nanotechnology has dramatically changed 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 2000–2003 (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 key words in cities over time. Instead of counting and comparing the raw number of entry and exit, which would not account for differences in size of the different fields, we focus in our analysis on the rate of entry, exit or maintenance. Assuming that the spatial dynamics of knowledge in a given field can be defined as an evolving 2-mode network based on pairs of city-topics (Boschma, Heimeriks and Balland, 2014) we compute the maintenance rate as the share of city-topics linkages in t that are maintained in t+1.

Figure 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), very stable over time. Although nanotech was the least stable field in 2000 (below 0.1), its maintenance rate increased importantly over time, and it is now comparable with organic chemistry (above 0.25). Biotechnology also started with a low level of stability, and it is still a very dynamic field characterized by both a high level of entry and exit of topics in cities.

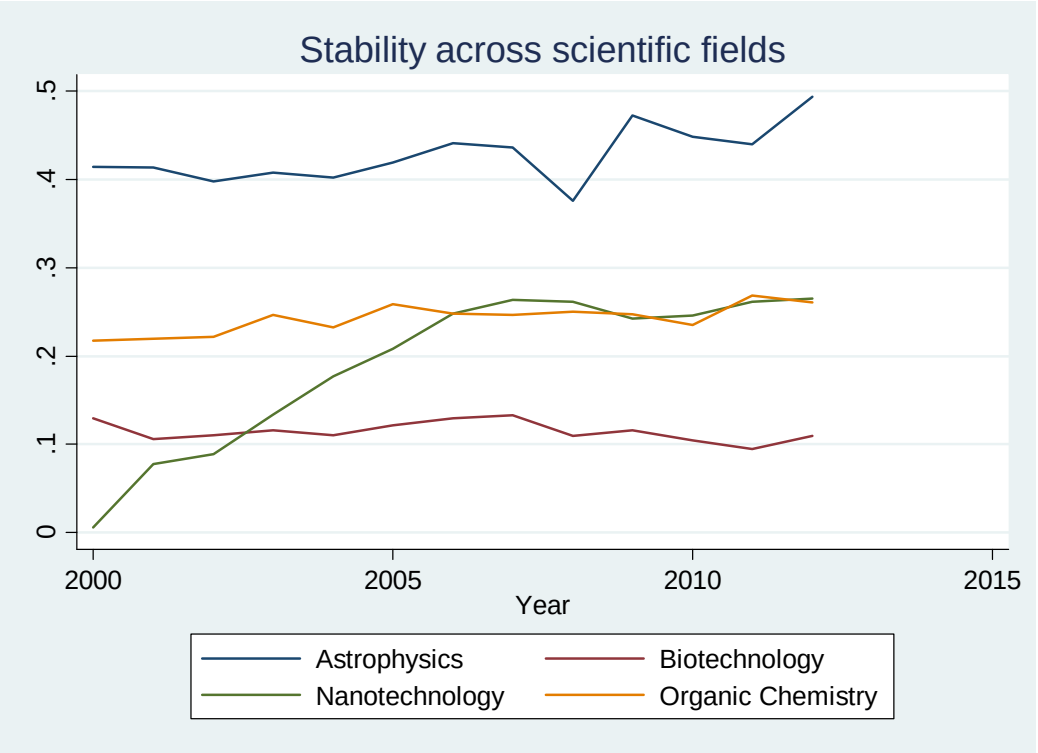

Figure 6. Maintenance

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. In the next section we further investigate the ease of search, within fitness landscapes by modelling the interaction between knowledge components through relatedness between 2000 and 2010.

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

5.1 The model

We want to estimate how relatedness influences in a different 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' 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 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:

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

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 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 4 different fields. Therefore we run 4 different models, one for each field, with the same econometric specification and compare the size of the standardized $relatedness\_density_{i,c,t-1}$ 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 level. $City_{c,t-1}$ is a vector that summarizes a range of observable time-varying city characteristics: city (scientific) size and specialisation. The scientific size is computed as the number of key-words 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 summarizes a range of observable time-varying technology characteristics. In our empirical analysis we only account for topics size, 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 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 1000 topics (key-words) for each scientific field over the period 2000-2012 (2-year period). Table 3 provides some summary statistics of the variables used in the econometric analysis.

Variables	Obs	Mean	Std. Dev.	Min	Max
Astrophysics					
Entry	637731	.1533374	.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	.0292736	.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	.0657978	.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	.0746417	.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

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

Table 3. Summary statistics

5.2 Entry model

Table 4 presents the results for the estimation of equation 4 for each of the 4 scientific fields separately. 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 the fields that we analysed exhibits in some extent a pattern of path and place dependence. In that respect we confirm and extend the results of Boschma, Heimeriks and Balland (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 (β=0.0820; 95% 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 confidence intervals 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 level.

The control variables (city size, topic size, specialisation of cities) tend to show the expected sign and significance (Table 4). An increase in city size also increase the probability of entry (of any new topic) in all fields (not significant at the 5% level for Astrophysics) excepted 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 of entry for Astrophysics and Biotechnology, while it is not significant in Nanotechnology and it has a negative impact for Organic Chemistry.

Dependent variable is: Entry	**Astrophysics**	**Biotechnology**	**Nanotechnology**	**Organic Chemistry**
Relatedness density	.0820996**	.0079124**	.0168617**	.0210179**
	(.0009077)	(.0003302)	(.000845)	(.0006255)
City size	.00000293	-.0000571	.0000663**	. 0000476**
	(.00000170)	(.00000936)	(.00000444)	(.00000640)
Topic size	.0000894**	.0000913	.0007438**	.0004785**
	(.00000511)	(.000056)	(.0000189)	(.0000331)
Specialisation	.0000639**	.0000144**	.00000377	-.0000699**
	(.000013)	(.00000232)	(.00000228)	(.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

Notes: The dependent variable entry = 1 if a given topic (n = 1000) enters the scientific portfolio of a

*given city (n = 200) during the corresponding 2-year window (n = 4), and 0 otherwise. The "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 the *p < 0.05; and **p <0.01 level. Heteroskedasticity-robust standard errors (clustered at the city-technology level) in parentheses.*

Table 4. Entry dynamics in the 4 different fields

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 exit dynamics for each of the 4 scientific fields separately. 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 importantly 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 level.

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 (Table 5). Once we relax the fixed effects, the coefficient is negative and significant again. In all cases, large topics tend to remain longer in cities (not significantly for Biotechnology). Specialisation has always a negative impact on the probability of exit but it is only significant in the cases of Astrophysics and Biotechnology.

Dependent variable is: Exit	**Astrophysics**	**Biotechnology**	**Nanotechnology**	**Organic chemistry.**
Relatedness	-.1733424**	-.0239141**	-.0271512**	-.0576634**

density	(.0031749)	(.0030116)	(.0051883)	(.0006255)
City size	.00000198	-.0001571*	.0000294*	-.00002
	(.00000133)	(.0000738)	(.0000126)	(.0000134)
Topic size	-.0000355**	-.0001451	-.0001761**	-.0002417**
	(.00000398)	(.0001715)	(.0000239)	(.0000302)
Specialisation	-.0006563**	-.0001919*	-.0000704	-.0001556
	(.0002468)	(.0000784)	(.0000581)	(.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	0.1344	0.0540	0.1224	0.0996

*Notes: The dependent variable exit = 1 if a given topic (n = 1000) exits the scientific portfolio of a given city (n = 200) during the corresponding 2-year window (n = 4), and 0 otherwise. The "relatedness density" variable is standardized so it can be compared across models. All independent variables are lagged by one period. Coefficients are statistically significant at the *p < 0.05; and **p <0.01 level. Heteroskedasticity-robust standard errors (clustered at the city-technology level) in parentheses.*

Table 5. Exit dynamics in the 4 different fields

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). The past decades has seen a remaking of the map of world science and innovation, as countries including China and South Korea have increased their investment and risen up the league tables of papers published. At the same time, many new topics were introduced in scientific articles. Governments, both nationally and regionally, need to ensure that the local knowledge base is strong to ensure global competitiveness (Foray 2006).

Our research shows that fields differ markedly in the possibilities for specific locations to become and remain competitive. New research topics in Biotechnology create short lived comparative advantages for a small number of locations. In contrast, in Astrophysics research locations have more capabilities to contribute to a diversified set of topics. In the case of Nanotechnology, new locations contribute new topics, but some existing locations maintained a prominent role. In summary, the fields show different levels of path dependency (maintaining a comparative advantage over time) and different levels of place dependency (concentration of research topics in a number of location) giving rise to distinct co-evolutionary dynamics of specialisation.

The analyses presented here have major implications for research and innovation policy with respect to the local knowledge base. The innovation systems literature emphasizes 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 localized knowledge dynamics that can be expected to respond differently to government interventions.

Our analyses show that the variety of topics that are (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 into account identifying related variety. 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 it to nurture new research activities. This is all the more important today, because of ongoing globalisation.

It remains necessary to further research the actual cause of the observed local comparative advantages. These advantages can be expected to result from existing routines, infrastructures and skills in the research organisations. Creating a

competitive advantage may entail different strategies in stable fields with high levels of mutual dependence among researchers than in turbulent fields with lower levels of mutual dependence and high levels of task uncertainty.

For example, in some fields (Astrophysics) it may be possible from a policy perspective to define a set of priority topics which are likely to be important for years to come, while in other fields (Biotechnology) this approach can be expected to fail. Likewise, 'picking-winner' policies in terms of research locations are more likely to be successful in a stable field with well-known infrastructural requirements that help contributing to diverse sets of topics (Astrophysics) than in turbulent and fast growing fields (Biotechnology). These results are similar to the Schumpeterian patterns of innovation that are found to be technology-specific (Malerba & Orsenigo, 1996).

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 journal representing an entire field. Inevitably, part of the observed changes in the field can be attributed to journal specific dynamics. As such, this methodological issue requires more attention. Nevertheless, we expect that the observed changes also reflect the dynamics of the fields to a large extend, because the results are in line with previous studies (e.g., Heimeriks & Leydesdorff 2012).

6. 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 organisations can be attributed to their specialisation pattern of scientific knowledge production.

The analyses showed that in all fields, path and place dependent processes of knowledge production can be identified. 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 and infrastructures), and that a research location can only contribute to topics for which it has all the requisite capabilities.

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. However, these patterns are remarkably similar across locations within each scientific field. Two patterns of specialisation are identified. The first represents a turbulent pattern: concentration of research activities is low, knowledge producing organisations are of small size 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 specialised in certain topics face high levels of uncertainty in exploring new topics.

The second represents a stable pattern: concentration of research activities is higher than in the first group, research locations are of larger size, stability in the ranking is greater, and comparative advantages last longer. Relatedness among topics is high, and the locations that are specialised in certain topic 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 coincides with the surge in funding of nanotechnology between 2000–2003 (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. These patterns are clearly related to available repertoire of related topics in the different fields. Looking at the entry of new topics, we can see that Astrophysics is the most path dependent field. In relative terms, Biotechnology is the least path dependent and Nanotechnology and Organic Chemistry show intermediate level of path dependence. Likewise, the exit of topics shows that the most path 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.

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 (β=0.0820; 95% 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). Smart specialisation strategies need to take into account the two dependencies that this study brought to the fore. In accumulative fields of knowledge production, were research locations have the capabilities to contribute to many (related) topics, the number of new entrants tends to be low. The key policy is to identify the commonalties and infrastructures in these fields that allow for diversity in knowledge production. Reversely, in fields where locations contribute to a small number of topics (relatedness is small), there are more opportunities for new entrants to establish a niche for themselves. Policy should focus on developing a narrow set of research activities in order to yield greater innovative output.

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Appendix

Year	Entry_orgchem	Exit_orgchem	Maintenance _orgchem
2000	.8730593	.7822831	.2177169
2001	.8343939	.7804756	.2195244
2002	.8571656	.7783604	.2216397
2003	.9207658	.7537555	.2462445
2004	.7563099	.7674155	.2325846
2005	.8808065	.7411945	.2588055
2006	.7629339	.7518477	.2481523
2007	.7749474	.7533503	.2466497
2008	.7206201	.75	.25
2009	.8085558	.7524852	.2475148
2010	.6916975	.7648863	.2351137
2011	.812393	.7313705	.2686295
2012	.7146627	.7389423	.2610577

Table 6. Knowledge dynamics in Organic chemistry

Year	Entry_nanotech	Exit_nanotech	Maintenance _nanotech
2000	.9447853	.993865	.006135
2001	5.425807	.9225807	.0774194
2002	1.592028	.9109027	.0890973
2003	1.552301	.8661088	.1338912
2004	1.363524	.8229942	.1770058
2005	1.057718	.7916778	.2083222
2006	1.316158	.7523325	.2476675
2007	.9671865	.7362712	.2637288
2008	.8596607	.7384887	.2615114
2009	.7197878	.757418	.242582
2010	.738438	.7544666	.2455334
2011	.874144	.738535	.261465
2012	.7544998	.7352216	.2647784

Table 7. Knowledge dynamics in Nanotechnology

Year	Entry_biotech	Exit_biotech	Maintenance _biotech
2000	.8477945	.8705769	.1294232
2001	.8606151	.8938492	.1061508
2002	.9712673	.889687	.110313
2003	.8818786	.8842505	.1157495
2004	1.080361	.8896814	.1103186
2005	.8710064	.8785942	.1214058
2006	1.114286	.8704225	.1295775
2007	.9718538	.8673568	.1326432
2008	.6965436	.8904511	.1095489
2009	1.006904	.8840843	.1159157
2010	.7252427	.8954692	.1045307
2011	.8865055	.9056162	.0943838
2012	1.00835	.8906561	.1093439

Table 8. Knowledge dynamics in Biotechnology

Year	Entry_Astro	Exit_Astro	Maintenance _Astro
2000	.741731	.5856768	.4143232
2001	.6616461	.5865893	.4134106
2002	.6057799	.6022627	.3977373
2003	.7022607	.5920907	.4079093
2004	.6390949	.598211	.401789
2005	.6795571	.5811344	.4188656
2006	.6787703	.5591606	.4408394
2007	.6107366	.5639592	.4360408
2008	.462931	.6241655	.3758344
2009	.902809	.5277154	.4722846
2010	.5587294	.5516478	.4483522
2011	.5574036	.5602772	.4397228
2012	.668927	.5066282	.4933718

Table 9. Knowledge dynamics in Astrophysics