Localized knowledge spillover and the emergence of new technology: the case of fuel cell technology development

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Abstract

For the past 20 years scholars have found support for the thesis that knowledge spills over in geographical and technological proximity to the source of knowledge creation. It is the objective of this paper to examine whether this understanding of LKS can contribute to a greater understanding of emerging technologies and their geographical distribution. The paper examines this by studying the emergence of fuel cell technology. It is argued that the fuel cell technology has potential to become a general purpose technology and the paper discusses what consequences this might have for knowledge spillover processes. The analysis is carried out on an OECD dataset on regionalized PCT patent applications (OECD REGPAT, June 2009).

The analysis focuses on knowledge production in FCs in the period 1992-2006. The results show: 1) that the spatial distribution of FC patents tends to agglomerate and 2) that this agglomeration pattern correlates to some degree with the general pattern of regional strengths in FC-related technology fields. These findings corroborate the usefulness of the theory on LKS in explaining elements of the emergence of new technologies. Moreover, the analysis sheds new light on regional development and diversification along new technological trajectory.

1 Introduction

This paper examines the geographical emergence of new technology and its possible linkages to regional knowledge strengths in related technology fields.

It is the overall thesis behind this paper that new technologies emerge geographically where the regional knowledge base complement the knowledge base of the new technology. This thesis has been studied other places in the literature as the cumulative nature of technological change (Nelson and Winter, 1982). The cumulativeness of technological change and knowledge production, in general, refers to the idea that new knowledge builds upon current knowledge. In this paper, I will argue that even in the case of the emergence of new technologies, which in fact is an expression of disruption and discontinuation of technological trajectories, knowledge generation still happens cumulatively.

Malerba and Orsenigo (2000) suggest that we can observe cumulativeness at various levels of analysis. In a micro level analysis we might find cumulative learning effects at the firm level, and at a more aggregate level, such as industrial sectors or larger geographical areas such as regions (meso level analysis), we might also find cumulative effects of knowledge generation. This paper focuses on the latter level of cumulativeness and investigates how regional knowledge bases of yesterday form the basis of knowledge generation today.

More precisely, I analyze two dimensions of the emergence of fuel cell (FC) knowledge production: One is the geographical dimension, where I investigate if the geographical distribution of FC patent applications across European NUTS3 regions agglomerates. Another is the dimension of technological relatedness in technological change, where I analyze if NUTS2 regions' cumulative knowledge bases can explain the geographical distribution of FC patent applications.

Patent applications to the PCT[1], is in this paper used as a proxy for knowledge production. Because patenting is a common way to appropriate knowledge in fuel cell technology development, I argue that patent applications under the PCT are a good proxy for measuring knowledge production activities. Whether or not a patent is granted, a patent application presupposes some kind of knowledge production activities to have taken place. Obviously, knowledge production also takes place without resulting in patent applications. However, at

[1] Patent applications filed under the Patent Corporation Treaty (PCT).

the aggregate level this analysis is carried out patent applications is seen as a good proxy for knowledge production.

The approach used in this study builds upon the literature on innovation systems derived from the field of evolutionary economics. In this approach the main activities are driven by actors who in interaction with each other generate, diffuse, and utilize knowledge to innovate (Nelson, 1993,Lundvall, 1992,Carlsson and Stankiewicz, 1991, Malerba 2004, Bergek and Jacobsson 2005). The innovative activities of firms are influenced by institutions, competences, and the knowledge base of the technology or industry. And in company's search and selection activities (Nelson and Winter, 1982), for instance choices made on who to collaborate with, or which R&D projects to start up, they determine the opportunities of knowledge production at a later stage.

In this paper I apply this overall understanding of innovation processes on the case of the emerging FC technology field and focus on the two dimensions: geography and the technology's cumulativeness of knowledge.

Fuel cell technology is an immature technology field in the sense that there is still some way before the technology is ready to penetrate the market. The technology, despite the benefits of being green, face severe difficulties in competing with the incumbent fossil-fuel based energy technologies. On top of that, other alternatives, such as batteries, and biogas add further uncertainty to the technological development path. However, the potential of the technology is by most assessed to be promising on the long-term. Not only in the transport sector (hydrogen vehicles), where the impact is expected to be greatest, but also in other product groups such as combined heat and power (CHP), backup power units, and in consumer goods such as laptops, and mobile phones, is fuel cells forecasted to have an impact. The wide variety of application opportunities and other characteristics such as a potential to grow large share of productive activities in the economy and strong technological complementarities in the development process suggest that fuel cells have potential to become a general purpose technology (GPT) (Lipsey, et al, 1998).

The many application options increase the opportunity conditions for the technological regime, but results in a diversified and complex development process, because knowledge of the technology and knowledge of market options has to go hand in hand (see also Malerba and Orsenigo, 2000). Also upstream is the technological development complex and depends on many complementary knowledge fields, that has to play together in order to overcome problems in penetrating the market.

This complexity calls to mind the externality of knowledge production that might ease and speed-up the innovation process because actors can access knowledge easier (because of reduced transaction costs). Bresnahan and Trajtenberg (1995) argue that in GPTs, knowledge spillover happen vertically, from the new GPT to the application sector, and horizontally, across application sectors. In the case of this paper I will introduce a third type of knowledge externality: Spillover from the current stock of knowledge into knowledge generation in emerging GPTs.

Based on an assumption that knowledge spillover is limited by the geographical distance to the source of knowledge, I test, whether I can confirm the existence of this third type of externality. In other words, if geographical proximity induces knowledge spillover from related technology fields into emerging technology fields.

In this paper I present the results of tests of two hypotheses, based on analysis of PCT patent applications following the two dimensions introduced above. First, I expect to find the geographical distribution of FC patent applications to be agglomerated regionally. The second hypothesis is that the frequency of FC patent applications, during a given period and in a given geographical region, is correlated with the existing knowledge stock of FC-related knowledge fields.

In anticipating the results, the test of the first hypothesis shows significant agglomeration patterns across Europe. The second part of the analysis confirms the cumulative nature of knowledge production at the regional level, also for an emerging technology field as FCs. For several of the measured fuel cell related technology fields (6 out of 8) I find a positive significant relationship to FC knowledge production at the regional level. This indicates that the regional knowledge base through regional learning dynamics have a great impact on a region’s opportunities to develop along new technological trajectory. A policy impact of these results is that regional innovation policies and strategies should build strongly on the regional knowledge base. Analyzing regional strengths and developing regional policies is a joint effort.

The paper is structured as follows. Section two accounts for the conceptualization of geographically localized knowledge production and introduces the concept of technological relatedness. Section two also specifies the research approach by formulating the two hypotheses this paper tests.

Section three outlines the characteristics of the FC technology and why it is interesting to study FC development in the light of the localized knowledge spillover frame. Section four presents the data and shows how the proxy of FC-related technology fields is interpreted and measured in this paper. Section five tests the first hypothesis on geographical agglomeration of FC knowledge and section six tests the second hypothesis on technological relatedness at the regional level. Section seven sums up the results.

2 Geographically localized knowledge production

In the economic geography and beyond, a great interest has been paid to the concept of localized knowledge production and learning (Boschma and Lambooy, 1999). In the pursuit of the truth about why economic activities are agglomerated in some regions and why some regions prosper more than others, economic geographers have studied the concepts of learning and knowledge creation in a geographical context. The interest in proving or showing the existence of localized learning effects is often seen as the key to explain why geography matters in the process of innovation.

The claim has been that co-location is an advantage for firms because it contributes to the company's innovativeness through easier access to knowledge. In particular, attention has been drawn to the tacit character of knowledge that makes this type of knowledge difficult to access over long physical distances. Because tacit knowledge is stored in the minds of scientists, researchers, industrial engineers and other knowledge workers the only way to access it is through direct communication, for example by doing research together. Hence, new economic knowledge within a given technology tends to agglomerate in geographical space.

In the stream of studies on the relationship between innovation and geography, researchers have found evidence of localized knowledge spillover (LKS) (Jaffe, 1989,Jaffe, et al, 1993,Feldman, 1999,Anselin, et al, 1997,Audretsch and Feldman, 1996,Feldman, 1994,Maurseth and Verspagen, 2002). These studies have more or less followed the same thesis and shown, in more or less sophisticated ways, empirical support for an association between innovation input and innovation output as an effect of geographical proximity. The studies differ in their use of proxies or measures for input and output as well as in their use of geographical units. But they all have in common that they confirm the overall hypothesis that knowledge production and innovation is to some extent associated with geographical proximity.

Knowledge spillover refers to the concept of knowledge externalities. Where efforts in knowledge creation carried out by some actors spill over and benefit other actors. The traditional starting point, for the literature on knowledge spillover, has been to add a spatial dimension to the knowledge production function (Acs and Audretsch, 2003,Audretsch and Feldman, 2004). In adding a spatial dimension to the knowledge production function, scholars have found stronger support at a broader level of aggregation, such as for countries or industries, than at the level of firms (Audretsch and Feldman, 2004). This finding suggested that something else influence the generation of innovation at the more aggregated level which is not present when we focus on the micro level alone. This something else has been seen as knowledge externality. And from this, the notion of knowledge spillover was born. A concept, that intends to explain the fact that we observe a higher innovative yield from R&D input at a more aggregated level.

Economic geographers have included other measures of proximity in studies of localized knowledge spillover. As Boschma (2004) argue, geographical proximity do not tell the whole story, but proximities such as cognitive, organizationally, institutionally and socially may complement, or substitute, the effect of geographical proximity. For instance, most of the studies mentioned above have included some kind of measure for cognitive proximity as a complementary explanation, by focusing on measures of technological relatedness in the knowledge spillover process. On the other hand, fewer studies have included direct measures of other kind of proximities, mostly because proximities of social or institutional kinds are very difficult to measure quantitatively. But no matter what complementary explanation has been included, the past 20 years' studies on localized knowledge spillover have found support of the hypothesis that knowledge spills over and that the spillover process is influenced by geographical and other proximities (Audretsch and Feldman, 2004).

However, the concept of knowledge spillover has been criticized for being imprecise when drawing the conclusion that the residual effect at the aggregated level is an externality (Breschi and Lissoni, 2001,Howells, 2002).

The main criticism is that, as the concept itself indicates, knowledge spillover is a notion of externalities, which is by definition a side effect of an economic transaction that benefit actors not directly involved in the transaction. But in the broad range of studies of LKS nothing has been done to isolate the effect of externalities as opposed to the effect of localized learning that derives from economic transactions, voluntary agreements on knowledge sharing, and other knowledge transferring channels.

As Zucker et al. (1998) show for the biomedical innovation system, the spillover effect is very low but at the same time the knowledge generation and entrepreneurial activities are co-located. They find localized effects of R&D input and human capital but they cannot confirm that this effect is due to spillover (externalities). On the contrary they find that the localized industrial benefit is caused by embedded tacit knowledge in star scientists who decide to start up own businesses in geographical proximity to their faculty laboratory. This result raises doubt about what is actually measured as spillover in the prevalent LKS studies.

The findings of Zucker et al (1998) and the critique raised by Howells, and Breschi & Lissoni (mentioned above) requires the concept of LKS to be modified. In fact the concept needs to be redefined under a new name in order to adequately encompass what studies of LKS measure. As Zucker et al. point out (2007) the findings in the above mentioned studies on LKS and in Zucker et al (1998) demonstrate *geographical localization of knowledge*, and not necessarily realization of knowledge spillover processes.

Geographical localization of knowledge might be induced by processes of knowledge spillover but could as well be market-based (e.g. user-producer interaction, consulting, contract research, licensing) or network based (e.g. R&D-collaboration, informal or formal networks mediated by trade associations) or entrepreneur-based (spin-offs and start-ups) (as Zucker et al (2007) showed). I recognize this clarification of the LKD-definition by Zucker et al. (2007) and see geographical localized knowledge, understood as knowledge production processes that might be enforced by localized externalities or by market-, network-, and entrepreneur-based knowledge flows that are geographically bounded.

However, it is not the scope of this paper to investigate the character of these *channels.* Instead I am interested in analyzing the geographical co-localization of knowledge in FC-related technology areas with FC knowledge production.

Despite this criticism, the tradition of LKS has contributed with a rich empirical tradition for measuring the relationship between geography and technological change. And it is my claim that this tradition of studying LKS, initiated by introducing the spatial dimension to the study of technological change, might show its usefulness despite that the content of the concept needs to be adjusted to what it actually measure.

Geographically localized knowledge production might take many forms, but for the sake of this study it is only the intention to indicate the relationship between geography and the localized knowledge production in fuel cell technology.

2.1 Technological Relatedness

As mentioned above other types of proximities are important in understanding geographical localization of knowledge. One of them is cognitive proximity.

Boschma and Frenken (2009) argue in their chapter on Technological relatedness and Regional Branching that knowledge spillover is more likely to happen between related economic activities than between unrelated. In related activities there exists the "right" level of cognitive proximity, which is a precondition for knowledge to be absorbed and used in new ways. And therefore, regions are more likely to develop and diversify into sectors, or technologies, that are closely related to their existing activities. One source, Boschma and Frenken refer to, is Neffke (2009), who states that there is some sort of coherence between the set of industries at the regional level. They cite Neffke: "regional portfolios of industries are not random, but rather a coherent set of related industries. This coherence is preserved over time as regions are more likely to expand into industries that are closely related to their present portfolio than into industries that are very dissimilar to their main economic activities." Neffke's point is in line with what Malerba (2000) calls the cumulativeness of knowledge at the aggregated level of regions.

In understanding the geographical emergence of new technologies the knowledge on regional diversification along related technological trajectories is of interest to study. And for this paper it supports the thesis, that new technologies emerge geographically where the regional knowledge base complement the knowledge base of the new technology.

2.2 Clarification of hypotheses

The theoretical considerations presented above form the understanding behind this paper's two hypotheses. The first hypothesis tests the geographical dimension of the emergence of fuel cell knowledge production and focuses on the geographical distribution and agglomeration of knowledge in fuel cell technology.

As I argued above, science and knowledge production is cumulative. Even for a new technology field as fuel cell technology I assume that knowledge in this field builds upon knowledge from related technology fields such as chemicals and basic electric elements. In other words I assume knowledge from these related technology areas feed into the development activities of FCs because of their cognitive relatedness. Because relevant knowledge input to FC development is spatially agglomerated I also expect to find FC knowledge production spatially agglomerated.

For that reason hypothesis 1 sounds: *I expect to find the geographical distribution of fuel cell patent applications to be geographically agglomerated.*

The second hypothesis focuses on the dimension of technological relatedness. In fact in this hypothesis I want to test the assumption behind hypothesis 1 as outlined above – if FC-related knowledge is co-located with FC knowledge production.

The test of hypothesis 2 is based on the empirical strategy used in the LKS approach. The literature on LKS has, based on a modified knowledge production function, found prove for a spatial dimension in knowledge spillover processes. The starting point for LKS studies has been the knowledge production function (Griliches, 1979) expressed as

$$KP_i = \alpha RD^{\beta}_i \, HK^{\gamma}_i \, \varepsilon_i$$

where KP stands for the level of knowledge production, RD represents R&D inputs and HK represents human capital inputs. The function follows the logic that knowledge production output is a function of knowledge production input.

In the literature on LKS, this function has been modified by adding a spatial dimension. In most cases this has been done by examining regions, or countries, as the unit of observation (i) instead of the single enterprise (in other cases it has been done by adding a measure for distance between the observed units - the firms).

For the sake of this paper, and to test the second hypothesis, I build upon the same logic as the theory on LKS. But I am not interested in the classical measures of knowledge production inputs (R&D and human capital). Instead, I want to test the thesis that co-located technological related knowledge is important in the development of emerging technologies. I have modified the knowledge production function to fit this logic:

$$KP_{FCi} = aRK^{\beta}_{i}\ \varepsilon_{i}$$

where KP_{FCi} represents the level of fuel cell knowledge production in region *i*, and RK represents related knowledge fields in region *i*.

The function expresses the thesis that cognitive and geographical proximity complements each other in the process of learning and in this way influences the technological development of regions. Cognitive proximity is measured as FC-related knowledge fields. The task in the second hypothesis is to investigate if there is a correlation between the existing knowledge base of the region and its high level of knowledge production in FC?

For this reason hypothesis 2 sounds: *The frequency of fuel cell patent applications, during a given period and in a given geographical region, is correlated with the existing knowledge stock of fuel cell related knowledge fields.*

Before turning to the test of the two hypotheses I introduce some characteristics and specific conditions for the emerging fuel cell technology in the next section.

3 The emergence of fuel cell technology

In this section I argue that the fuel cell (FC) technology has potential to become a general purpose technology (GPT) according to the definition by Lipsey, Bekar and Carlaw (Lipsey, et al, 1998). We will see that defining FC as a GPT might have consequences for the knowledge spillover processes that is at work in FC development. First I introduce some basic information on fuel cell technology and discuss how well the definition of GPT fits to the FC technology, and second I point out the anticipated knowledge spillover processes.

The fundamental knowledge of the basic principles in fuel cells dates back to the mid-19th century. But the recent wave of interest and effort in radically improving the technology has taken place over the last two decades. This improvement has allowed for testing and validating the technology by making prototypes and carrying out demonstration projects. This counts stationary power systems providing electricity and heat for households and offices; hydrogen fuel cell vehicles; and powering mobile phones and laptops.

The basic principle for the fuel cell is an electrochemical reaction between oxygen and hydrogen generating an electric current and water. The fact that the only emission from the fuel cell is water makes the technology an ideal alternative to the CO2-emitting energy technologies as long as the hydrogen used in the fuel cell, is produced from non-C02 emitting energy sources, e.g. wind or solar power.

The value chain of the fuel cell is rather complex because it branches out in several applications downstream. The importance of different types of knowledge varies across the different links in the value chain as well as across the various application opportunities. Nygaard (2008) shows how firms located upstream in the value chain rely on scientific knowledge to develop materials, polymers, catalysts and membranes. These firms provide knowledge to producers of fuel cell stacks and systems, and also to the related development around hydrogen storage tanks and dispensers. Because of the generic character of this knowledge, upstream firms operate in a range of diverse industries, and not only in fuel cells. Located in the heart of the value chain are firms who produce MEA (membrane electrode assembly) and fuel cell stacks as well as system integrators. Their knowledge is more based on application and is stronger related to engineering than basic science. Downstream in the value chain, we find energy companies, oil and gas companies and OEMs. They work on integrating the fuel cells into products, and use their advantages of being closer to the market. However, downstream companies also develop strong links to external partners, including universities and research centre (NYGAARD, 2008).

The FC technology is an interesting case for studies of emerging technologies. First of all, it can be argued that FC technology is an emerging general purpose technology. Following Lipsey et al.'s (1998) definition of a GPT there are four characteristics which should be fulfilled before a technology can be defined as a GPT: First of all, in its infancy, the technology should face much scope for improvement. Second, a GPT has a wide variety of uses, and third, a wide range of uses. And finally, a GPT have strong technological complementarities to existing or potential new technologies (Lipsey, et al, 1998).

How well does this definition fit to the emerging technology of fuel cells?

The first characteristic – the scope for improvement of FC technology – is clearly present. The biggest technological challenges FC faces, is to reduce costs and increase the level and stability of performance. In fact the scope for improvement is present in the whole value chain of FC production, from materials and component enhancement to stack and fuel cell development to integration in applications and enhancing performance and durability.

As indicated by Lipsey et al. (Lipsey, et al, 1998) it is through learning processes that costs are reduced and performance is increased. It is also through technological change and improvements of the technology that its feasibility to be applied in other sectors becomes relevant. This leads us to the second characteristic that needs to be fulfilled in order for the technology to be a GPT – its wide variety of uses.

For FC technology, technological deployment already takes place in many sectors, however, mostly still at a stage of testing and demonstration. First and foremost in the transportation sector, where hydrogen fuel cell vehicles have been produced, tested and continuously improved; but also in the utilities sector (e.g. combined heat and power systems), and in various back-up and auxiliary power units. Basically in every product that relies on energy, FCs have a potential. Thus, it also has a potential in the wide range of products that today rely on energy from batteries, e.g. mobile phones, laptops, forklifts, wheelchairs, shavers etc.

The third characteristic refers to the proportion of the productive activities in the economy using the technology (Lipsey, et al, 1998). It is obviously difficult to assess at this point in time, whether or not FC technology will fulfill the promises of the hydrogen economy as explained by Rifkin (2004) (see also Clark and Rifkin, 2006, Hisschemöller, et al, 2006, Hodson, et al, 2004, West, 2004 for a discussion on the potential and its possible realization,).

As indicated above the FC technology has clear potential to be applied to a variety of use. In fact the potential for FC technology lies in its capability to substitute and displace technologies that are essential for the incumbent fossil fuel based energy system, which the economy relies on today. And once the technology overcomes the technological obstacles on price, hydrogen storage etc. its high energy efficiency compared to fossil fuel based energy technologies indicates that the market pervasiveness is high.

The last characteristic of GPTs, technological complementarities, refers to the complex interdependency between components, materials and applications in the development of fuel cell technology systems. The knowledge base of the technology field is extremely complex and fuel cell development relies on many different knowledge areas. Knowledge fields such as electronics, chemical processes, materials science, and catalysts play important roles in fuel cell development. Also linkages to knowledge on the fuel input, hydrogen, methanol etc. is important knowledge fields and needs to be integrated in the developing of fuel cell systems.

FC technology is clearly not a GPT yet, since it only completes one of the four characteristics pointed out above, which ironically (but nevertheless always will be true for emerging technologies) is the scope for improvement. Nevertheless, it has a strong potential to fulfill the remaining three characteristics necessary to become a GPT. Even though the potential seems straight forward, the technological advances in fuel cell technology is surrounded by immense uncertainty.

Now I want to turn to the anticipated effect of FC being a GPT on the processes of knowledge production and spillover. Bresnahan and Trajtenberg (1995) note two distinct types of externalities for GPTs. One happens vertically, from the new GPT to applications and another horizontally across sectors. In this paper I will introduce a third type of knowledge externality: Spillover from the current stock of knowledge into knowledge generation in emerging GPTs. The idea behind this third type of externality origins from the literature reviewed above, that all new knowledge builds to a certain degree on current knowledge, in other words the cumulativeness of knowledge. Also for emerging technologies, such as FCs, the cumulative nature of knowledge production is important for technological change. I will argue that the cumulativeness of knowledge production is influenced by the degree of technological relatedness between the cumulated knowledge stock and the emerging technology. And in the case of FC development, that knowledge of FC-related technology fields is a precondition for entering FC knowledge generation activities.

This together with the notion of geographical localization of knowledge point to the two dimensions I intend to investigate in this paper: The dimension of geography and technological relatedness in knowledge production of FC technology.

4 Data and methodology

The main dataset used for this study is the 'OECD REGPAT June 2009'. The REGPAT dataset is the first comprehensive attempt to regionalize the distribution of PCT-patents[2] based on both inventors' and applicants' addresses (the REGPAT database also contains a similar dataset based on granted patent

[2] PCT= Patent Cooperation Treaty

filed to the European Patent Office, EPO). The PCT database covers approx 1.5 Mio unique patent applications in the period 1977-2007 (priority dates). For the purpose of this study focus is on the time span 1992-2006, because this is where the main activity in fuel cell patenting takes place. 2007 is left out because the data is not complete for this year. To identify fuel cell patents from non-fuel cell patents I use IPC-codes.

All patent applications are classified according to the International Patent Classification (IPC) system. IPC is a hierarchical classification system with 4 levels of grouping. The IPC is structured after 8 general patent classes (the letters A-H) which cover broad overall sections such as Human Necessities (A), Chemistry and Metallurgy(C) or Electricity (H). The next level is the subclasses that consist of one letter and two numbers, e.g. A43 Footwear, B01 physical and chemical processes or F22 Steam generation. Each of these 3 digit subclasses can be further divided into 4 digit groups by adding a letter, and so on, the highest level of classification contain 9 digits. At a 7-digit level we find the IPC code H01M008 corresponding to: "Fuel Cells; Manufacture thereof".

One patent is often classified under one main and one or more supplementary IPC-codes (9 digits). However, in the OECD REGPAT database it is not possible to distinguish between main and supplementary classifications. So for this study all patents with one or more hit in the IPC-code equal to H01M008 are included.

Figure 1 shows the development in FC patent applications to the PCT for the period 1992-2006 for all OECD countries. Total counts of patent applications with an IPC-code equal to H01M008 for this period equals 7.188. The development shown in Figure 1 illustrates an exponential development in the years 1992-2002; thereafter the growth seems to be constant.

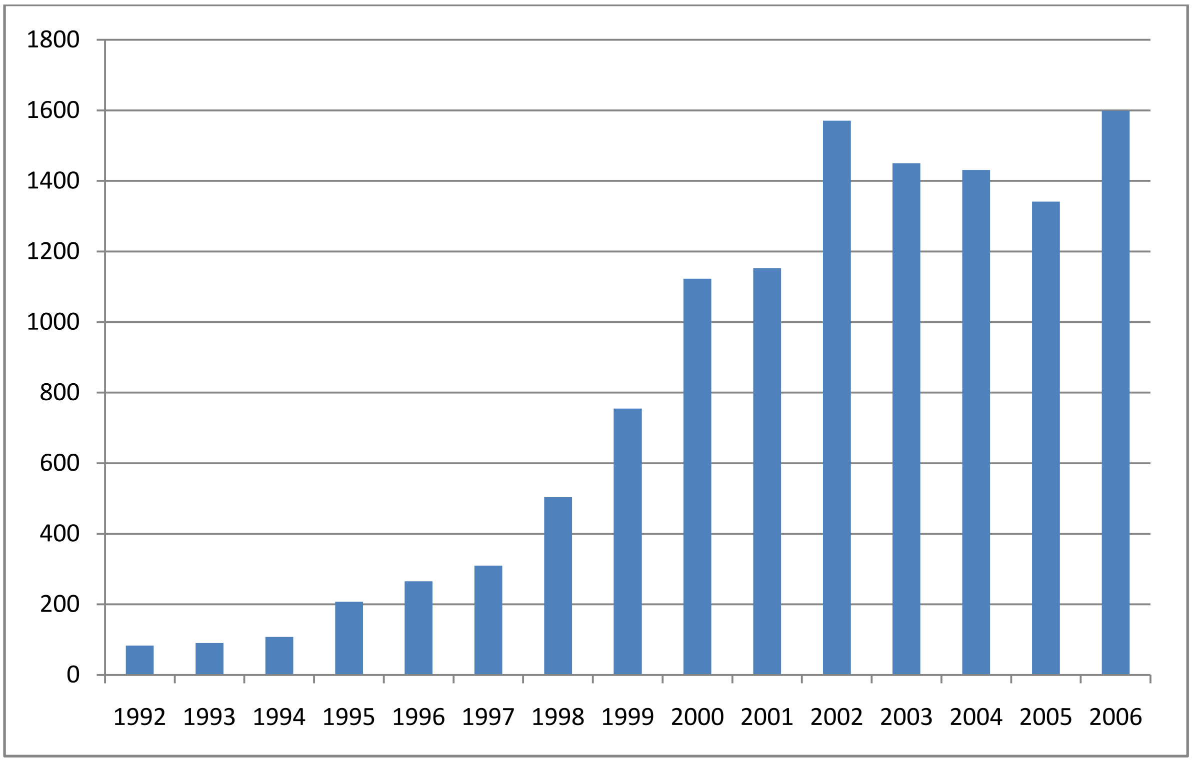

Figure 1: Development of PCT-applications 1992-2006 for patents with IPC codes equal to H01M008, source: OECD REGPAT June 2009

4.1 Identifying Fuel Cell related technology fields

In this section I identify the technology fields that are related to FC development. I do this by analyzing the technology fields (IPC-codes) FC-patents are co-classified with. These technology fields are interpreted as a proxy for FC related knowledge fields, and are assumed to feed into FC technology development. I use these technology areas in the test of hypothesis 2 (the dimension on technological relatedness).

As mentioned above patents often receive more than one IPC code, because they cover more than one technology area. Figure 2 shows the frequency of co-classifications for FC patents at the subclass level (3 digits). Figure 2 illustrates the IPC subclasses that FC patents most often are classified under in the period 1992-2006. If a patent has 4 IPC-classes where two 9-digits IPC-codes are covered by the same IPC subclass this knowledge area is only counted once.

All IPC co-classifications with a share larger than 2 % is included in a measure of FC related technology areas.

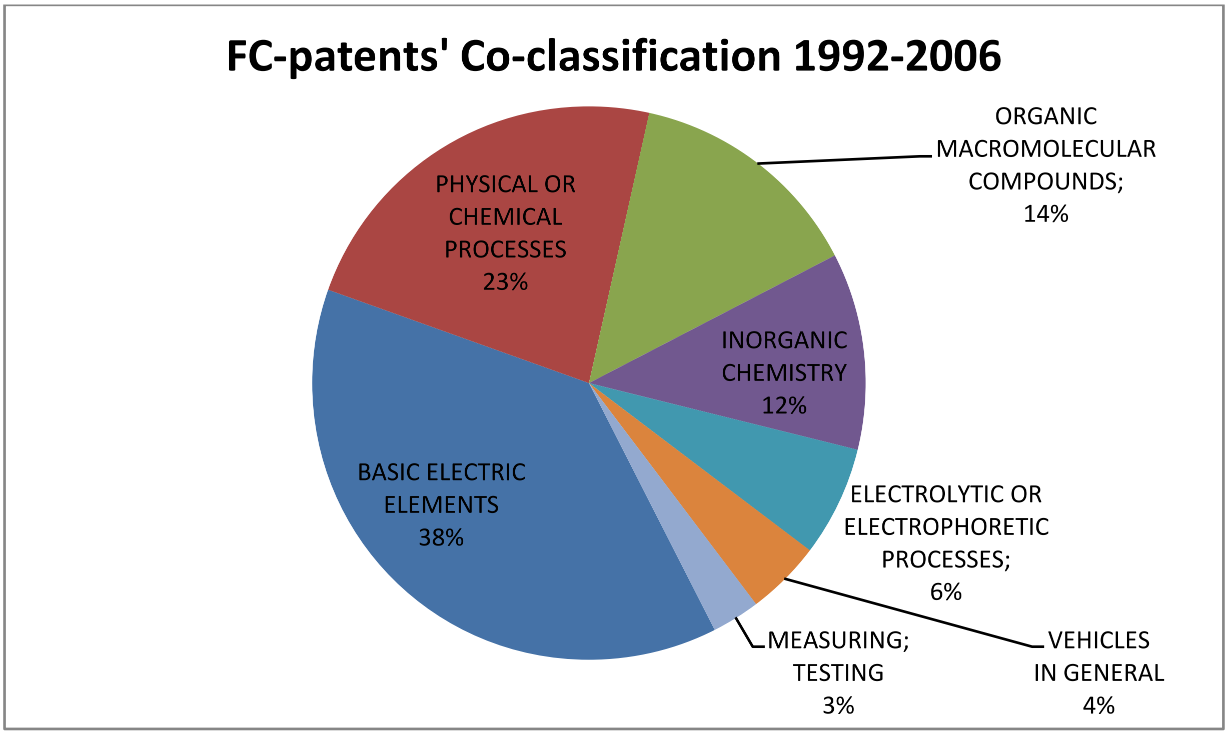

Figure 2: FC-patents' co-classifications, H01= Basic Electric Elements,

A section on the various knowledge fields and where and how they are relevant in FC development will be added later.

Figure 3 shows the development over time in the distribution of co-classifications. As seen, the distribution is relatively stable, however it is noticed that the share of 'Vehicles in General' is growing while electrolytic processes are decreasing. The increase in 'Vehicles in general' indicates a stronger involvement of actors from the automotive sector and that the technology is becoming more mature and ready for applications and in this way closer to market stage.

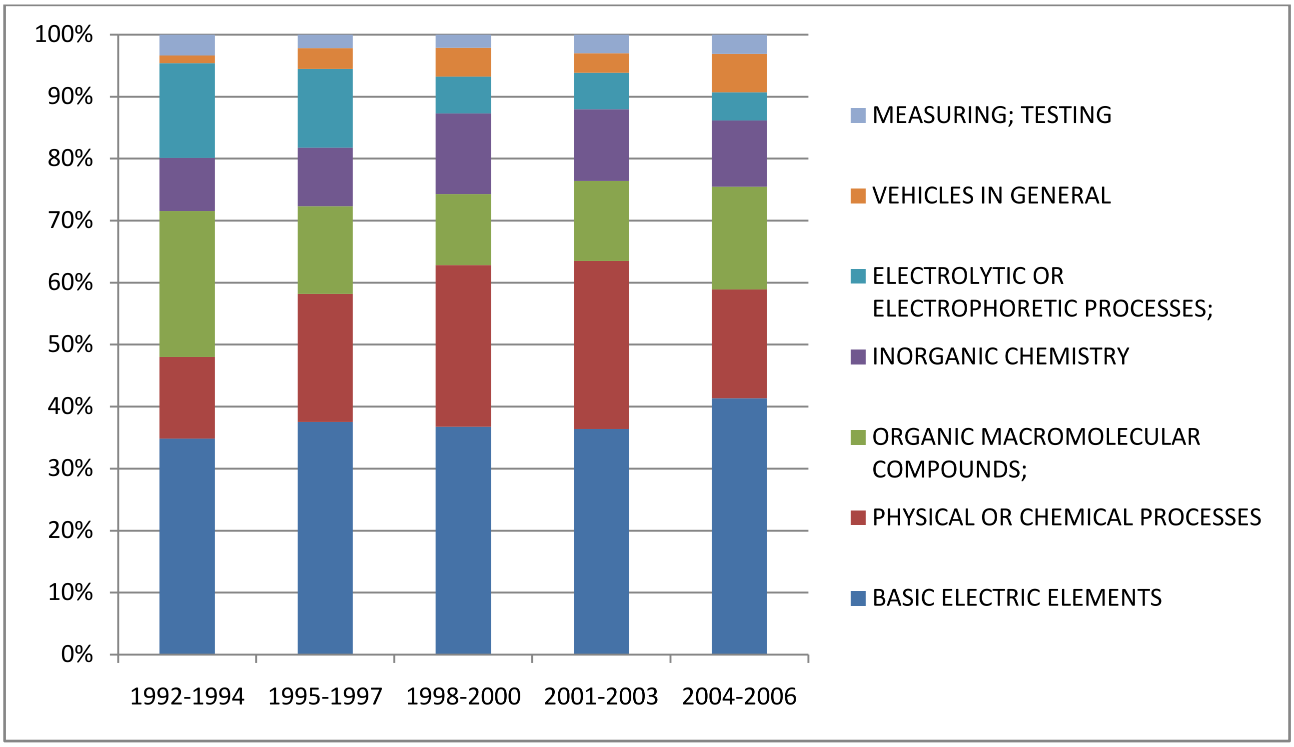

Figure 3: Development of the distribution in FC-patents' co-classifications (IPC subclasses)

4.2 Regional level

After this short descriptive presentation of the data, there is one more thing I will touch upon before turning to the analysis of the hypothesis – the regional level of analysis.

The territorial grid OECD uses in the REGPAT database is the Territorial Level 3 (TL3), for Europe this corresponds to regions at NUTS3 level[3].

In this study I have chosen to focus the analysis on European regions alone. However, I make use of both the regional division at NUTS-level 2 and 3.

In the first test of the geographical distribution of FC knowledge I carry out the analysis on NUTS3. Because my unit of analysis is the region and I want to test whether or not FC knowledge is geographically agglomerated it is useful to apply this analysis on the smallest possible regional size. By using the smallest regions (NUTS3) as units it is possible to show how these regions cluster into larger regions with high activity in FC development.

[3] NUTS stands for 'Nomenclature of Units for Territorial Statistics' and is defined by the European Union.

In the second hypothesis, it is on the other hand more useful to carry out the analysis on NUTS level 2 or higher. Because I am interested in the geographical localization of knowledge and possible co-localized learning effects a larger territorial division is necessary. To use the spillover term, the optimal regional size for testing hypothesis 2 is the one that captures as much of the interregional spillover and least of the intraregional spillover as possible. For this study I have decided on NUTS2. However, in a later study it would be of interest to analyze the differences in spillover across varying levels of regions.

5 Geographical dimension of FC knowledge production

In this section I investigate the geographical dimension of FC knowledge production and test the first hypothesis: *If the geographical distribution of fuel cell patent applications is geographically agglomerated.*

To test the geographical autocorrelation of FC-patents applications I have extracted the European regions (NUTS3) from the whole dataset. Figure 4 illustrates the spatial distribution of FC patent applications based on inventors' address across Europe. Unit of observation is based on NUTS3 regions. The map clearly shows that FC patent applications are not evenly scattered across Europe. To test if this immediate interpretation of the data being agglomerated holds I have run a global and local test of spatial autocorrelation.

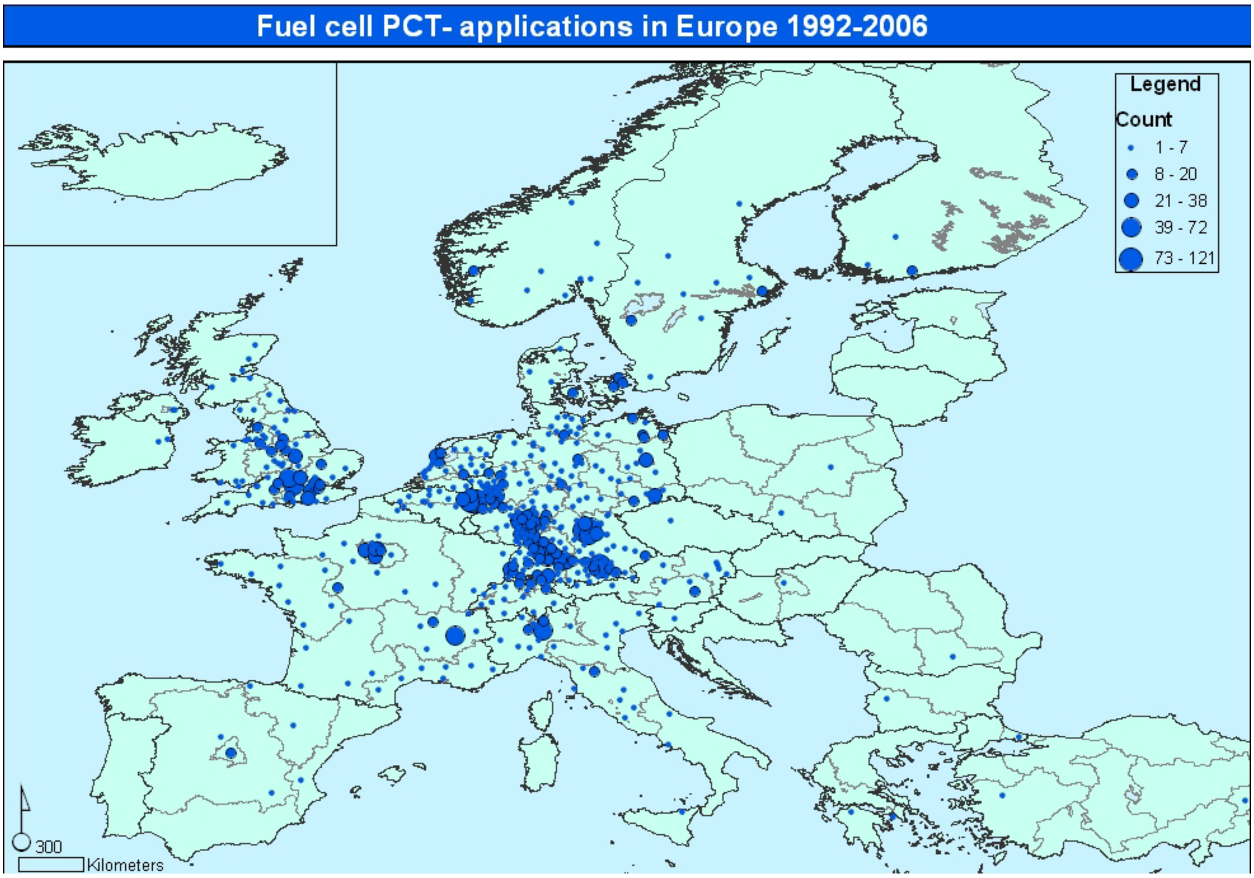

Figure 4: Geographical Distribution of Fuel Cell PCT-application in Europe 1992-2006, source OECD REGPAT June 2009,

I have calculated the univariate Moran's I for FC patents applications from 1992-2006 using the geospatial analysis software GeoDa^{TM}. The Moran's I is a measure of spatial autocorrelation. A negative Moran's I indicate a negative spatial autocorrelation and a positive indicate a positive correlation. The values range from -1 (perfect dispersion) to +1 (perfect correlation). I found Moran's I values around 0.39, using different types of spatial weights, among these a queen contiguity weight (all borders and points in common) and K nearest neighbor (K=5, every region is set to have 5 neighbors). The Moran's I of 0.3963 indicates a positive correlation (see figure 5 below). Moran's I is calculated on NUTS3 regional level to show if neighboring regions at this level tend to cluster and if it is possible to identify larger regions (e.g. at NUTS2 level) that show high activity in FC knowledge production.

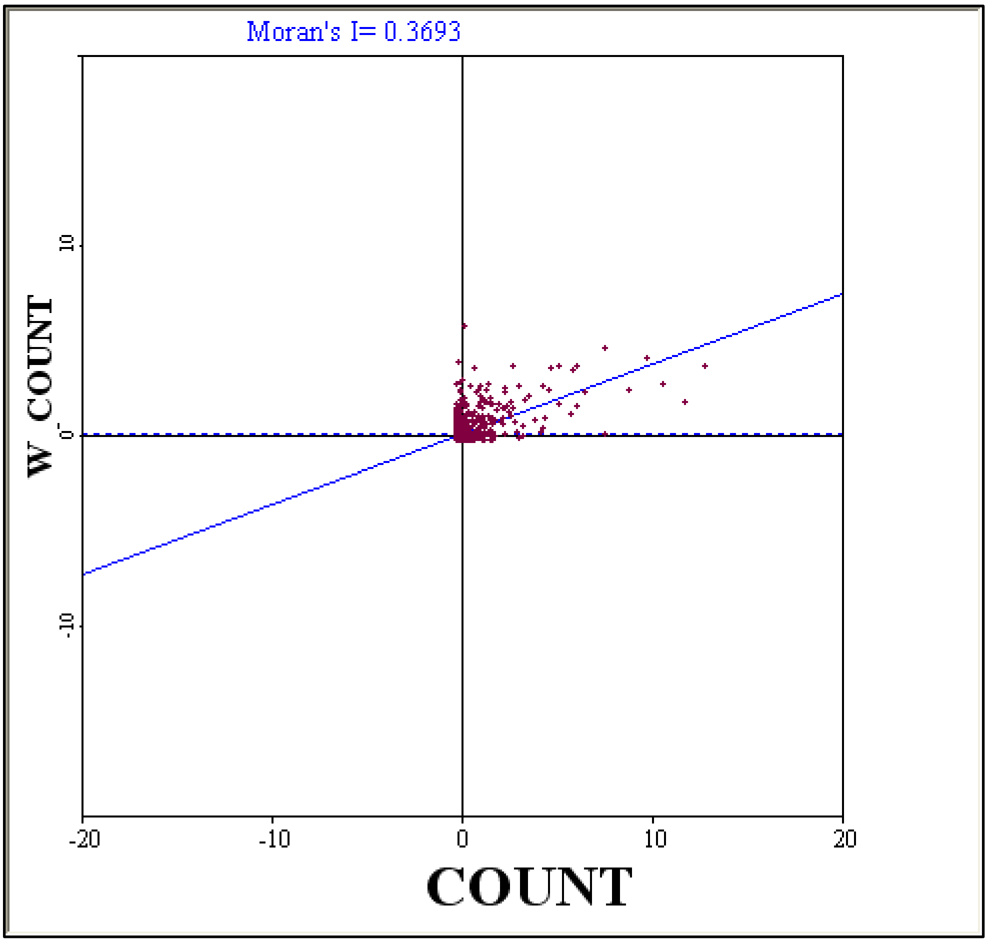

Figure 5: Moran's I based on queen contiguity weight

To illustrate the spatial autocorrelation I have produced a LISA cluster map (local spatial autocorrelation), as shown in figure 6. Where the Moran's I is a measure for the global spatial correlation, the LISA cluster map illustrates the local spatial relationship for regions with FC knowledge production. This map illustrates how neighboring regions are correlated. The four color codes on the map illustrate how regions with FC-patents applications and their neighbors score together. If the color is dark red the region itself and its neighboring region are both scoring high, if it is dark blue neighboring regions are scoring low-low, pink for high-low, and light blue for low-high. In other words the four colors correspond to the four quadrants in the Moran's I scatter plot (Figure 5). The map shows clear signs of clustering of high-level regions in South and Western Germany as well as in South England around London. On the other hand the dark blue colored regions in Eastern and Southern Europe indicate clustering of low knowledge production.

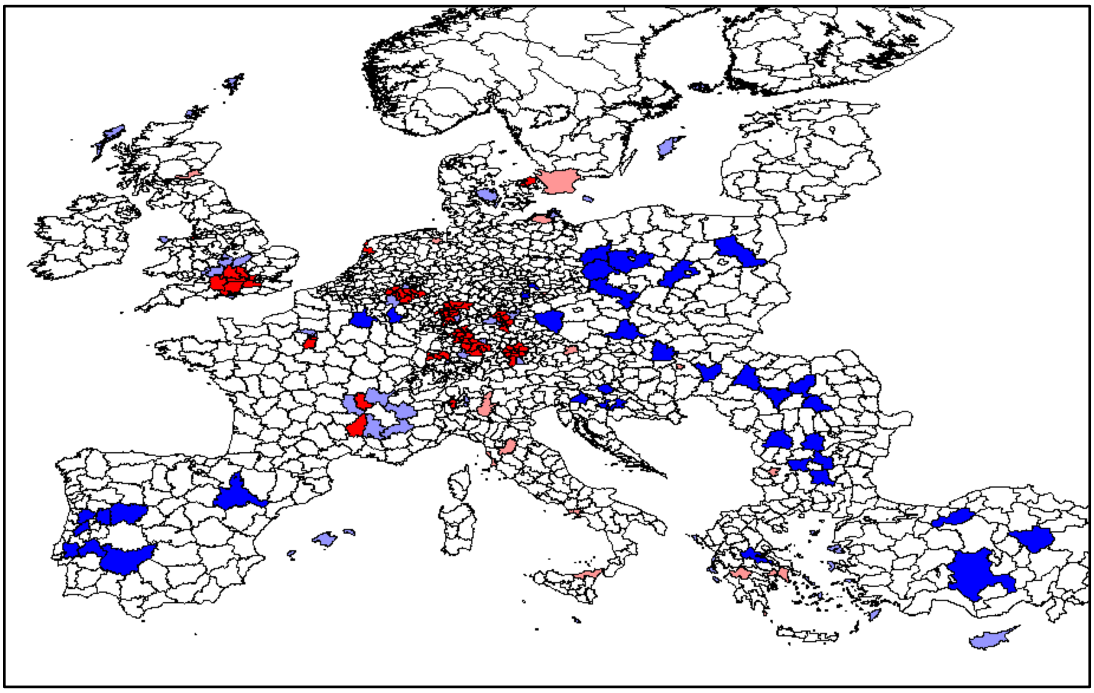

Figure 6: LISA cluster map for 1992-2006 based on total FC patent applications counts at NUTS3 level. Statistical Significance <= 0.05

The Moran's I and the LISA cluster map confirms hypothesis 1: That FC knowledge production, measured by FC patent applications, tends to cluster in certain regions.

In the next section I test one of the assumptions behind this finding: If geographical agglomeration of FC knowledge production is statistical associated with the presence of certain FC-related knowledge fields.

6 Technological relatedness in FC knowledge production

In this section I analyze the dimension of technological relatedness in FC knowledge production by testing hypothesis 2: *The frequency of fuel cell patent applications, during a given period and in a given geographical region, is correlated with the existing knowledge stock of fuel cell related knowledge fields.*

The data was prepared by following this procedure: First, I extracted all FC-patents applications for the years 1990-2006, each patent application was counted once if they had one or more IPC-codes (7-digits) equal to H01M008. Second, I extracted all non-FC patents applications for all regions for the same period 1990-2006. These data was summed based on the IPC- subclass (3 digits) to indicate the quantity of knowledge produced in a given field in a given region. As a consequence one patent application covering more subclasses has been counted more than once. For instance, if one patent application was classified under three different subclasses (e.g. H01, B01, and B60) it would correspondingly receive one count in each of these subclasses. This is done to measure the presence of this knowledge field in a particular region.

The data analysis is carried out on panel data comprised of data for each of the years from 1990-2006 for each of the 256 European NUTS2 regions[4]. The dependent variable is knowledge production in FC and the independent variables are the related technology fields in all non-FC patent applications (see Section 4.1, Figure 2 for the defined related technology fields).

Most of the 256 regions have low rates of FC patent applications while few regions have higher rates. See Table 1 for list of variables and summary statistics:

[4] The analysis includes NUTS2 regions from the following countries: Austria, Belgium, Switzerland, Check Republic, Germany, Denmark, Spain, Finland, France (without Guadalupe), Greece, Hungary, Ireland, Iceland, Italy, Nederland, Norway, Poland, Portugal, Sweden, Slovakia and United Kingdom.

Table 1: Variable names and summary statistics

List of variables	European NUTS2 regions				
	N	Mean	S.D.	Min	Max
H01M008; Fuel cell patent applications (PA)	4352	1.20	5.05	0	91
H01; Basic Electric Elements (PA)	4352	18.68	54.91	0	786
B01; Physical or chemical processes(PA)	4352	12.88	30.61	0	335
C08; Organic Macromolecular compounds(PA)	4352	14.91	45.15	0	773
C01; Inorganic Chemistry(PA)	4352	2.85	7.62	0	103
C25; Electrolytic or Electrophoretic processes(PA)	4352	1.22	3.70	0	63
B60; Vehicles in General(PA)	4352	11.69	45.21	0	1018
G01; Measuring, Testing(PA)	4352	23.39	54.23	0	659
C04; Cement, Ceramics, etc. (PA)	4352	2.14	5.44	0	71
Tot_tech; Total count (PA)	4352	416.50	854.16	0	7376
FC Knowledge stock	4352	6.82	29.87	0	442
H01 Knowledge stock	4352	135.48	427.61	0	6702
B01 Knowledge stock	4352	107.101	282.79	0	3589
C08 Knowledge stock	4352	115.26	390.70	0	7340
C01 Knowledge stock	4352	22.44	60.86	0	903
C25 Knowledge stock	4352	10.54	28.33	0	374
B60 Knowledge stock	4352	84.047	341.30	0	8439
G01 Knowledge stock	4352	179.58	444.62	0	6229
C04 Knowledge stock	4352	18.28	44.27	0	556
Total Knowledge stock	4352	3225.29	7411.49	0	88267

The dependent variable is a count variable and suggest the use of a count model. As noticed in Table 1, S.D>mean which suggest not to use the simple Poisson model but to use the negative binomial model. I therefore analyze this data using a negative binomial regression with fixed effects in the Stata 11.0 statistical package. Both a random effects and a fixed effects model have been estimated and tested by running a Hausman test. The Hausman test was rejected and suggests the fixed effect model.

In order to have a more precise measure of the existing knowledge stock of FC-related knowledge fields I have calculated the cumulated stock of non-FC patent applications within each of the FC related technology areas; see Table 1 for summary statistics.

Table 2: Technological related knowledge stock effects on FC patenting, Negative Binomial Regression with fixed effects for European Regions (NUTS2), 1990-2006

Explanatory variables All in log[5]	**Fuel Cell knowledge stock**	
H01 Knowledge stock	0.855***(0.079)	0.678***(0.0863)
B01 Knowledge stock	0.543***(0.096)	0.266*(0.1056)
C08 Knowledge stock	0.270***(0.069)	0.238***(0.0721)
C01 Knowledge stock	0.323***(0.0543)	0.308***(0.0588)
C25 Knowledge stock	0.014 (0.042)	0.025 (0.0477)
B60 Knowledge stock	0.118*(0.526)	0.138*(0.597)
G01 Knowledge stock	-0.178^(0.101)	-0.099 (0.1147)
C04 Knowledge stock	0.149**(0.057)	0.181**(0.063)
Total Knowledge stock	-0.462**(0.168)	0.215 (0.186)
Constant	-2.727***(0.616)	19.719***(0.171)
Population		-1.427***(0.171)
R&D-Total (GERD)		-0.856***(0.0923)

Note: Dependent variable: Fuel cell cumulated knowledge stock, measured as patent applications to the PCT. Unit of analysis is NUTS2 regions in Europe, 26 groups dropped because of only one observation or zero observations per group. Significance levels: ^0.10, *0.05, **0.01, and ***0.001. Knowledge stock is calculated as cumulated patent applications with one IPC-code equal to the related technology field.

Table 2 shows the results of two models: one without any control variables and one with Population and Government R&D expenditure[6] as control variables. The results shown in Table 2 confirm that some technology areas have a positive impact on the regional FC knowledge stock. The technology fields: basic electric elements (H01), physical or chemical processes (B01), Organic Macromolecular compounds (C08), Inorganic Chemistry (C01), Vehicles in general (B60), Ceramics (C04) all have a positive significant association with the FC knowledge stock. It is interesting to notice that the electrolytic and electrophoretic processes (C25) is not significant, which is the technology field with a decreasing share of co-classifications over time, as was shown in Figure 3. It is also interesting to note that the total knowledge stock for all knowledge fields has a negative significant effect without controls on FC knowledge production and does not show any significance when the controls are included.

[5] Because of the large variation and huge range for some of the independent variables I have taken log to the independent var.

[6] For the data on Government expenditure on R&D (GERD) single years were missing for several regions. For these years, and to prevent losing data I have interpolated data based on the mean of the previous and subsequent years' GERD. Source: OECD and Eurostat.

These findings are interesting seen in the light of the findings of Zucker et al. (2007). They show that the cumulative stock of all given knowledge have a positive significant effect on nanotechnology articles and patents. This might indicate differences between the two emerging technology fields.

To sum up the analysis in the paper, these preliminary results indicate a confirmation of hypothesis 2 for 6 out of 8 technology fields. However, in future work it is my ambition to refine the model by following two tracks:

1. Improve the statistical model by more tests to be sure that this model has the best fit.
2. Include more control variables. One challenge, when working on regional statistics, is that it is difficult to get access to balanced panel data for variables that could be interesting to control for, such as educational level, high technology manufactures etc.

7 Concluding remarks

This paper has analyzed the relationship between geographically localized knowledge and the emergence of new technologies. I have sought to test two hypotheses on the relationship between geography, the development of FC technology, and related technology areas. I believe it is important to increase our understanding of how emerging technologies evolve and which factors influence this process. If regional knowledge bases play an important role in shaping the future technological opportunities for a given region, as these results indicate, it is of great importance to consider this in the development of regional innovation policies. In other words, regional innovation policies and strategies should build strongly on the regional knowledge base.

This paper has provided the following results based on the analysis of FC patent applications:

1. The analysis in Section 5 has shown that FC knowledge production tend to cluster in regions.
2. This paper has applied an LKS-approach (cited in Section 2) on the field of emerging technologies. The analysis in this paper has indicated that FC-related knowledge fields and FC knowledge is geographically co-located, indicating the regional knowledge base complement the knowledge base of new technology development.

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